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THESIS

ANALYZING THE SURFACE WARFARE OPERATIONAL EFFECTIVENESS OF AN OFFSHORE PATROL VESSEL USING AGENT BASED MODELING

by

Jason L. McKeown

September 2012

Thesis Advisor:	Paul Sanchez
Second Reader:	Eugene Paulo

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With the increasing emphasis of asymmetric tactics employed by terrorist organizations and extremist militants, the development of fast and capable naval combatants has become the focus of many navies around the world. Predominately aimed at the defense of the littorals, these smaller naval combatants must be able to establish maritime dominance at an affordable price, given constrained defense budgets. The Offshore Patrol Vessel is one such ship type that can meet these needs.

This thesis explores the development of a Map Aware Non-Uniform Automata agent based simulation in an Anti-Surface Warfare environment. Insights gained through the models indicate that OPVs placed in a small boat swarm scenario will be hard pressed to successfully defend an object if not sufficiently armed to combat the threat. While the weapon systems placed on OPVs have a significant impact on simulation results, additional factors indicate that interactions between associated OPV systems and outside contributors are also vital.

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Jason L. McKeown
Lieutenant, United States Navy
B.S., Oregon State University, 2006

Submitted in partial fulfillment of the
requirements for the degree of

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September 2012

Author: Jason L. McKeown

Approved by: Paul J. Sanchez
Thesis Advisor

Eugene Paulo
Second Reader

Robert F. Dell
Chair, Department of Operations Research

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ABSTRACT

With the increasing emphasis of asymmetric tactics employed by terrorist organizations and extremist militants, the development of fast and capable naval combatants has become the focus of many navies around the world. Predominately aimed at the defense of the littorals, these smaller naval combatants must be able to establish maritime dominance at an affordable price, given constrained defense budgets. The Offshore Patrol Vessel is one such ship type that can meet these needs.

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LIST OF ACRONYMS AND ABBREVIATIONS

ASCM	Anti-Ship Cruise Missile
ASNET	Application System for Naval Evaluation and Testing
ASW	Anti-Submarine Warfare
ASUW	Anti-Surface Warfare
CCS	Central Control Station
CDR	Commander
CIC	Combat Information Center
CIWS	Close In Weapon System
CO	Commanding Officer
COG	Center of Gravity
COL	Colonel
DDG	Guided Missile Destroyer
FFH	Fast Frigate with Helicopter
GT	Georgia Institute of Technology
LCDR	Lieutenant Commander
LCS	Littoral Combat Ship
LH	Latin Hypercubes
LT	Lieutenant
LTJG	Lieutenant Junior Grade
LTTE	Liberation Tigers of Tamil Eelam
LWL	Length at Waterline
JMP	John’s Macintosh Project
MANA	Map Aware Non-Uniform Automata
MILSPEC	Military Specification
MIO	Maritime Interdiction Operations
MOE	Measure of Effectiveness
MOP	Measure of Performance
M/V	Motor Vessel
NATO	North Atlantic Trade Organization

NICOP	Naval International Cooperative Opportunities in Science & Technology Program
NPS	Naval Postgraduate School
NOLH	Nearly Orthogonal Latin Hypercube
PRONTO	Partnership for Research on Naval Technology and Operations
PT	Patrol
OEMs	Operational Evaluation Models
OLH	Orthogonal Latin Hypercube
ONR	Office of Naval Research
OPV	Offshore Patrol Vessel
OR	Operations Research
OSN	Orrizonte Sistemi Navali
RA	Research Assistants
RAM	Rolling Airframe Missile
ROC	Risk of Collision
SAM	Surface to Air Missile
SAR	Search and Rescue
SEED	Simulation Experiments & Efficient Designs
SFAC	Small Fast Attack Craft
SLOC	Sea Lanes of Communication
SSM	Surface to Surface Missile
SWO	Surface Warfare Officer
UI	User Interface
U.S.	United States
USS	United States Ship
VT	Virginia Polytechnic Institute of Technology
WWI	World War 1
WWII	World War 2

EXECUTIVE SUMMARY

The overall objective of this thesis is to assist the Office of Naval Research (ONR) and its support of a research effort undertaken by Orrizonte Sistemi Navali (OSN), an Italian naval ship construction organization. OSN's work is focused on the development of naval ship dashboards, capable of facilitating discussion between ship designers and decision makers. Centered on the Offshore Patrol Vessel (OPV), these dashboards utilize a series of Operational Evaluation Models (OEMs) and Ship Synthesis Models to help decision makers understand the trade-space involved with naval ship architecture. The Anti-Surface Warfare (ASUW) scenario being modeled in this thesis is a part of the OEMs, along with several other mission areas such as Search and Rescue (SAR), Maritime Interdiction Operations (MIO), and Cost Estimation. These models feed the OEMs and subsequently, the dashboard, which then displays OPV performance in each mission area for a particular equipment setup. This performance indication can then be adjusted to assist decision makers as to which areas may need more attention, or which areas can be lowered in importance.

This thesis provides an evaluation of key performance factors of a theoretical OPV in an ASUW Scenario. To model the scenario, agent based modeling software was used to construct both the OPVs and the small boat swarm threat to create an environment capable of exploring a wide range of factors and associated levels. The New Zealand developed agent based modeling software, Map Aware Non-Uniform Automata (MANA) was chosen to generate the agent based models necessary for data collection purposes. The simulations conducted are divided into two primary sets. The first set is the baseline simulation which focuses on establishing interchangeability with a provided OSN model, as well as determining factor baseline importance. The second set of simulations diverges from the baseline model to explore a larger sample space to identify possible emergent behavior and changes in factor importance and interactions.

Establishment of interchangeability between the OSN model and the baseline model generated in MANA is important because it helps to verify the work performed by OSN. Verification eliminates the possibility that the results produced by the OSN model

are a result of sampling error or other unknown factors. Aside from verification, interchangeability provides a basis for follow-on factor comparisons. If the models are interchangeable, then if one model possessed an additional capability, the other model would be expected to produce similar outcomes if it also had the same capability. This forms the basis of the advanced models which follow the baseline MANA modeling effort.

The advanced modeling effort initially focuses on creating a more challenging scenario for the modeled OPVs. The number of opponents that the OPVs face has been increased, as well as the introduction of behaviors available in the MANA modeling software. These behaviors are Avoidance and Aggression, and their inclusion in the advanced scenarios is intended to show how agent movement impacts OPV performance. To follow the increases in the small boat threat, the OPVs are also enhanced to reflect a more realistic naval platform seen at sea today. These changes are then evaluated to see how they impact the more challenging small boat problem.

Results and insights gained from the baseline modeling effort indicate that the models are interchangeable with the inclusion of an indicator variable. The naval gun is clearly the most significant factor with nearly 80% of all variance accounted for by this factor alone. Following this is the type of surface-to-surface missile system equipped on the OPV. Additionally, the inclusion of the helicopter helps to provide tactical data to the OPVs, and directs them to the nearest small boat threat for quicker prosecution. The results gained from the baseline effort seemed to stress an increase in OPV armament to increase the response, with very little impact from interaction terms or other factors.

The advanced models indicate a divergence from the insights gained from the baseline models. Given that the small boat threat possessed the capability to either evade or attack OPVs, then the speed and mast height factors, and their interactions, became more significant in relation to the number of small boat kills. In the enhanced OPV simulation runs, the naval gun significantly dropped in importance when compared to the missile system since its accuracy now reflects historical performance when engaging seaborne targets. The most significant factor was the type of small boat being engaged by the OPVs, followed by the equipped missile system on the OPVs. Ultimately the advanced models indicated that an agile ship with good radar capabilities to feed information to its associated missile systems would be the most capable at combating the small boat swarm threat.

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This thesis would not have been possible without the person who introduced me to the topic, Dr. Eugene Paulo. He always provided support and words of encouragement to help keep me, and the other OR students involved with the ASNET/PRONTO NICOP, motivated in accomplishing our goal.

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Finally, I'd like to thank my wife, Stephanie, for always supporting me when things got tough, and for always holding down the fort at home during my late nights here at school. Her love and understanding form the bedrock of the man I am today.

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I. INTRODUCTION

The Offshore Patrol Vessel (OPV) is one of the fastest-growing naval ship classifications in the world today. As of 2009, there were 23 nations worldwide operating OPVs with 76 in production or on order at a value of over $10 billion according to the "Offshore Patrol Vessels: Sector Report, 2009" (OPV Sector Report, 2009). The following year, those figures grew to 30 countries employing OPVs with another 89 in production and plans for 98 at a value of over $15 billion, "Offshore Patrol Vessels: Sector Report, 2010" (OPV Sector Report, 2010). This begs the question, why the OPV class and not the destroyer or frigate, which are larger and generally more capable? While frigates are regarded as the smallest class of ship that can operate independently on the open ocean, the smaller OPV requires less manning and maintenance, while still adequately performing the same mission capabilities (Mommsen, 2009). This results in reduced costs for naval ship production and maintenance, which is very appealing to smaller nations given tightening budget constraints.

Figure 1. Comandante Class: ITS Comandante Foscari (P-493)

Primarily focused on the Anti-Surface Warfare (ASUW) and Anti-Submarine Warfare (ASW) side of national security, OPVs fit into a growing national need of power projection and military capability. This military contribution is relevant due to national waterway and resource disputes as neighboring nations vie for rich resource grounds, be it fishing, trade, or offshore drilling. The territorial dispute in the South China Sea is a good example: “The importance of the South China Sea as a strategic passageway is unquestioned. It contains critical sea lanes through which oil and many other commercial resources flow from the Middle East and Southeast Asia to Japan, Korea, and China” (Snyder, 1996). To assert a nation’s territorial claims they must have a presence in the region, and warships have traditionally been the facilitators of that presence. Aside from power projection, OPVs have increased in popularity over the recent decades due to their capabilities in Maritime Interdiction Operations (MIO) and Search and Rescue (SAR), which predominately fall into the roles of the coast guard. Unlike the U.S., which separates its coastal and naval forces, many nations utilize their navies to fulfill both roles. OPVs are a great asset for this capability, and for the smaller nation, modern OPVs provide an adequate projection of naval power at a relatively cheap price.

The OPV is also appealing due to its reduced manufacturing costs when compared to other combatants. OPVs are generally built in two separate fashions, the first being a higher cost military variant stressing weapon systems, while the other is for generally more peacetime operations. The second variant is aimed toward commercial and civilian specifications rather than military ones to reduce costs. The reason behind this shift is to help ease the fabrication and system operating requirements that military specifications (MILSPEC) impose on naval vessels and designers. Considerations as to ship damage survivability and system redundancy are stressed more so in MILSPEC vessels than commercial vessels. Commercially oriented ships tend to focus more on crew habitability and survivability, thus creating a cheaper platform to produce. Thus for a nation with tightened budgets for military spending, the OPV provides flexibility given its prescribed mission.

A. BACKGROUND

During the summer of 2008, Ms. Kelly Cooper, Program Officer at the Office of Naval Research (ONR), attended the EURO SIW, International Simulation Multi-Conference concerning innovative studies applied for the estimation of naval ship effectiveness. It was at this conference that Ms. Cooper met Dr. Natalino Dazzi, a project manager of Orizzonte Sistemi Navali (OSN), which is a leader in Italian warship operational design and production with ties to other international markets. Dr. Dazzi and his OSN staff were presenting their work on research activities and innovative studies applied for estimation of the naval vessel effectiveness in regards to mission task, cost, and performances. Interested in this topic, Ms. Cooper speculated whether the same efforts could be applied to current U.S. ship modeling efforts. A dialog between the two was created and in early December 2010, a workshop was held in Rome with ONR and OSN, to begin a project focused on techniques and tools to facilitate discussion between decision makers on naval ship design, particularly on an Italian OPV. The project was titled the Application System for Naval Evaluation and Testing (ASNET), Partnership for Research on Naval Technology and Operations (PRONTO), Naval International Cooperative Opportunities in Science & Technology Program (NICOP). Its mission is the linking of the Operational Evaluation Model (OEMs) and Ship Synthesis Model to better provide information for customers and streamline this ship building process. ONR's interest is the possibility of broadening this research for use in the U.S. Navy and its own ship construction endeavors. The Naval Postgraduate School (NPS), Georgia Institute of Technology (GT), Virginia Polytechnic Institute of Technology (VT), and several other organizations have been brought in to work on this project.

Tapped as the project lead for the NPS effort in the ASNET/ PRONTO NICOP, Dr. Eugene Paulo, of the Systems Engineering Department, identified the need for operations analysts to be included in the endeavor. This analytical role was filled by several Operations Research (OR) master's students and Research Assistants (RA), as well as faculty from the Simulation Experiments & Efficient Designs (SEED) Center for their simulation and computational capabilities. Each OR master's student would approach a particular mission area of the simulated OPV, conduct analysis on the OSN model outputs, and expand their models to encompass further research questions. The mission areas addressed were Anti-Surface Warfare, Maritime Interdiction Operations, Search and Rescue, and Cost Estimation. With the exception of the cost estimation, each OR student was provided with an OSN generated agent based model and its associated data to form a basis for their research efforts.

B. RESEARCH QUESTIONS

This thesis is based on the simulation modeling of a hypothetical OPV, to provide insightful information to decision makers on naval ship design and procurement. This insight is gained by the generation of dashboards that receive input from their associated models. The dashboard currently in development at the Naval Postgraduate School is focused on the linking of naval operational models to ship synthesis models. Prior to their inclusion into the dashboard however, the models would be required to perform in such a manner, as to produce results that are both believable and realistic. The models developed in the course of this thesis are focused on answering the following questions:

1. Based on the limited number of design parameters of the OPV in the OSN model, can a model be produced in the Map Aware Non-Uniform Automata (MANA) (McIntosh et al., 2012) environment to replicate similar results?

2. Given the creation of this initial MANA model of the OPV's ASUW scenario, can additional variables be introduced to determine a better Operational Evaluation Model for OPV performance and subsequent input into the Ship Synthesis Model and cost models?

C. SCOPE OF THE THESIS

This thesis focuses on the Anti-Surface Warfare scenario presented by the OSN modeled OPV. Guided by the previously presented research questions, the modeling effort first focused on the creation of the OSN ASUW scenario in the MANA environment. Second, once model behavior was established to be behaving adequately compare to the OSN agent based model, additional factors were introduced to gain further insight on the importance of key factors in the OPV design. MANA version 5 was utilized to model both the baseline scenario and more advanced scenarios. Analysis of the baseline scenario would need to show its interchangeability with the OSN agent based model, as well as establish a benchmark for key performance factors of the modeled OPVs. The advanced models analysis ascertains if these key performance factors change in the new scenario environments, and identify areas of investment to further enhance OPV technologies. Once the analysis is completed, the conclusion and recommendation portion of this thesis explains why these changes occurred, and present insights as to optimal OPV configurations for the ASUW scenario.

D. THE ASYMMETRIC THREAT

While the specifics of the scenario are detailed later, the overarching problem that is addressed in these models is the small boat swarm attack. Research work concerning this topic has been of increasing frequency given the asymmetric tactics employed by terrorist organizations and militaries still operating in the world today. The attack on the USS COLE on October 12, 2000, while she conducted refueling operations in Yemen is a stark reminder of how effective a single small boat laden with explosives can be against a ship.

Figure 2. USS Cole (DDG-67) Being Towed to its Rendezvous With M/V Blue Marlin

Another example of effective asymmetric tactics is the Sri Lankan Civil War. The Tamil Sea Tigers, utilizing asymmetric tactics such as suicide boats and swarming maneuvers, were effective in engaging in a civil war for almost three decades, where they inflicted heavy loses to the government sponsored Sri Lankan Navy. Only by enhancing strategies and military capabilities of its navy was Sri Lanka able to claim victory over the Liberation Tigers of Tamil Eelam (LTTE) on May 17, 2009. This victory was largely due to the effective isolation of LTTE strongholds by cutting all sea lanes of communication (SLOC), thus preventing outside resupply of resources and weapons. To do this, Sri Lankan naval forces employed fast attack craft and OPVs to establish multiple barriers of defense to both defend from Sea Tiger attack swarms and prevent retreating LTTE forces from escaping (Fish, 2009).

Apart from actual conflict, study of Iran's naval doctrine against future adversaries has shown that asymmetric tactics will be the focus to defeat larger, more capable outside aggressors in naval engagements, such as the U.S. Navy. In wartime, Iranian naval forces would seek to close the Strait of Hormuz and destroy forces bottled up in the Persian Gulf; therefore speed and surprise would be key (Haghshenass, 2006). To achieve this, Iran has been focusing on the acquisition and development of small, fast weapons platforms, particularly lightly armed small boats and missile armed fast attack craft (Haghshenass, 2006). Additionally Iran has been encouraging decentralized decision making practices in its naval forces, to further enhance and support its naval swarm tactics.

All of the previous examples present a very real and current threat that has to be addressed by the navies of the world today. Presuming a navy adopts strategies to combat swarming threats and other asymmetric tactics, the next question would be as to what technology would best combat the problem. Contenders would surely be small, fast, patrol craft that can cover range at speed and in volume. Additionally they would have to be supported by persistent, wide-area surveillance systems, most likely airborne in nature (Mallon, 2011). The OPV is one of the ship classes that can meet these requirements.

E. SCENARIO OVERVIEWS

1. Baseline Scenario

The OSN provided scenario consists of an established combat area where three OPVs perform a defensive role against approaching Small Fast Attack Craft (SFAC). It is the mission of these SFACs to reach a goal line which is protected by the three OPVs. The OPVs are equipped with a varying array of weapons and capabilities to employ in this goal line defense. The type of SFACs and their associated starting area are also varied to create a random battleground for the OPVs to perform in.

The specific capabilities of the OPVs that are varied include missile type equipped, the presence of a naval gun, maximum speed, and mast height which impacts the detection and classification range of the OPV. Weapon hit probabilities and ranges are fixed, and are specific to the associated weapon. Additional to the ship capabilities, the presence of a helicopter, which assists the OPVs by detecting and classifying SFACs and relaying target data, is introduced to half of the modeled scenarios. The OPV patrol routes, starting locations, and patrol speeds are fixed for the initial modeling effort. OPVs, and the helicopter if present, relay targeting data perfectly with an unlimited communication range. If SFACs are detected, the OPVs accelerate to maximum speed and attempt to intercept and destroy them. In the absence of SFAC detection, OPVs return to, or continue, their established patrol route at the prescribed patrol speed.

The SFACs varied parameters focus on their max speed and size, which impacts the range at which OPVs and the helicopter can detect and classify them. SFACs are randomly generated in a home box in the modeled environment, and the probability of their random location distribution in the box is uniform. There are nine total SFACs in the scenario, and for the initial modeling efforts, this is a fixed parameter. SFAC behavior is also fixed, in that they proceed to the goal line at max speed on the shortest route possible. They are not influenced by outside factors such as the OPVs or nearby SFACs. SFACs hit by OPV weapons are eliminated from the battle, and this information is gathered by the OPVs instantaneously.

2. Advanced Scenarios

In the effort to better understand the importance of key factors determined in the baseline scenarios, the modeling space has been increased to accommodate additional behaviors and factors. The reason is to see if these previously determined factors change in importance, or if other factors become more significant. Increasing the realism of the baseline scenario has to be done with caution however, as it may produce results that may be misleading or shed no useful information to the problem of the OPV effectiveness. It can be problematic if particular factors are varied individually which result in no significant change to the response of the advanced model. This can lead to the conclusion that these factors are not important, yet it may be true that the interactions of these varied factors cause a significant change in the response. Sanchez (2006) uses capture-the-flag as an example, where speed and stealth are varied to their high and low set points, but are not varied jointly. The end result is that neither factor changed the response by itself. If the interaction of speed and stealth was not explored, then a reader may conclude that neither speed nor stealth will help in capture-the-flag, while direct observation says otherwise when both are varied together.

For the advanced scenarios, addressing the behavior of the SFACs was of interest to the OSN staff when this thesis was in its initial phases of development. They were very interested in the possibility of varying tactics that SFACs could take as they approached the OPVs, and to see the results of the OPV response. The strategy to investigate this increase in SFAC behavior is a stepped process. First, the avoidance behavior is introduced to the SFACs, which means they now can detect and attempt to avoid OPVs as they proceed toward the goal line. Second is the aggressive behavior, where SFACs detect and attempt to attack OPVs utilizing a suicide weapon. Finally, a combination of both avoidance and aggressive SFACs are introduced for OPVs to prosecute. The goal for this scenario is to see if OPVs are drawn away or otherwise preoccupied to prevent avoidance SFACs from reaching the goal line. Once these scenarios are run, another set of the same scenarios are conducted, but with OPVs with enhanced capabilities more in line with real world situations. Many of these capabilities are drawn from previous theses such as Abel’s (2009) study on frigate defense effectiveness in asymmetric environments.

In each of these scenarios, the number of SFACs has been doubled from nine to eighteen. The reason for this change is to stress the OPV's ability to defend the goal line, and to refocus the study from the measure of effectiveness of the OPVs of successful goal line defense, to the measure of performance of weapon and system effectiveness.

F. CHAPTER OUTLINE

Chapter II is the literature review portion of the thesis, and it provides insight on current published references that have greatly impacted this research effort.

Chapter III contains the methodology and data portion of this study. It details specific parameters in the models created, as well as differences present between the provided OSN agent based model and the NPS generated MANA model. Also, limitations and assumptions were addressed, as well as the measures of effectiveness for the scenario.

In Chapter IV, produced data was analyzed to gather and understand important information and outcomes. Initially this chapter establishes the interchangeability of the OSN model to the NPS baseline model, and identifies which parameters are of the most significance for OPV performance. Following this, the advanced model analysis ascertains whether or not previously identified significant factors remain so, or if other factors become more noteworthy.

Chapter V is the conclusions and recommendations portion of this study. It provides the overview of the analyzed data, and produces recommended OPV configurations to meet the ASUW scenario. Additionally, it provides possibilities of future work to help expand and grow this analysis to encompass a larger sample space, and more realistic factor set points.

G. BENEFITS OF THE STUDY

This thesis is in support of the ASNET/PRONTO NICOP Project as part of ONR's support of the OSN OPV design effort. The modeling and analysis conducted helps to provide a better picture as to key design parameters in the ASUW role of the developing OPV. Additionally, the work conducted may help to identify areas of concern or technology gaps to invest in prior to actual ship construction. Upon completion of the project, analytical processes, and ship design considerations will be utilized by ONR to help in further U.S. naval ship modeling and construction efforts.

II. LITERATURE REVIEW

A. INTRODUCTION

This chapter covers the principles and practices that are most relevant to the OPV modeling situation and how published works contributed to this study. Since this thesis revolves around a naval surface warfare scenario, it is important to analyze established naval surface warfare doctrine and how it applies. Additionally, the dilemma being addressed in the modeling environment, the small boat swarm attack, is a current and realistic threat to both naval ships and strategic national assets, such as ports, oil derricks, and vital shipping lanes. There is a wealth of published works regarding this threat, and this thesis draws on several theses regarding the strategy. Understanding the principles used in agent based modeling is important as well, and this thesis references and expands upon previous works utilizing many of the same techniques. Finally, the overall effort of the ASNET/PRONTO NICOP project is intended to facilitate discussion and give direction in naval ship production, therefore understanding historical practices in ship building is important.

B. NAVAL WARFARE DOCTRINE

Before any topic concerning naval doctrine can be written, a firm grasp as to the specific context of the word "doctrine" is important. The word "doctrine" can be defined as a set of beliefs which are held and taught by an associated group, such as a church, government, or other such organization. The term naval doctrine then implies that it is a set of beliefs held and taught concerning naval tactics and practices by a navy. Vice Admiral Luigi Donolo, in his publication, *The History of Italian Naval Doctrine* (1995) defines it as:

> …the set of principles, rules (and also beliefs and values) which indicate what that navy must be, who or what it must represent, how it must behave and for what future perspectives it must prepare itself.

The U.S. Navy's definition in Naval Doctrine Publication 1: Naval Warfare (1994) is similar:

> Naval doctrine is the foundation upon which our tactics, techniques, and procedures are built. It articulates operational concepts that govern the employment of naval forces at all levels.

Other nations also have comparable definitions for their naval forces, and the underlining principle gathered from these doctrines, is that they are forged from a nation's historical actions at sea, and the impacts that they have had on military and political interests.

C. SWARM TACTICS

The term "swarming" is defined as the act of besetting or surrounding in a swarm. The noun "swarm" is defined as a large group of things, usually in motion. Thus it is the act of using motion, or speed, to surround something with a large number of other things. When related to combat studies and tactics, swarming occurs when several units conduct a convergent attack on a target from multiple axes (Edwards, 2004). Historical records show that some of the first military efforts employing swarming tactics date back to the time of Alexander the Great and Genghis Khan, where bowmen on horseback would swarm and encircle their opponents. Engagements in that time were made more difficult due to the need for quick and reliable communication between fighting elements. This is especially true with regards to coordinating swarm attacks due to the large number of elements and decentralized nature of command and control needed for the attack. Swarming has become even more prevalent in modern times due to its asymmetric nature, and partially because of the proliferation of mobile communication devices which helps to ease the coordination problem. The Battle of Mogadishu in October 1993 is a good example of swarming tactics being employed by an under-trained, under-equipped force utilizing simple coordination tactics to overcoming a superior trained and equipped enemy. For the focus of this thesis however, the small boat swarm attack is the overarching problem to be addressed.

Cobian (2002) studied the possible use of the Javelin weapon system for naval ship defense against small boat attack. He found that the weapon system possessed very high marks for probability of hit and kill at relatively low costs to eliminate a small boat threat.

				ISSUES / CONCERNS			SUPPO RT	USABLE PIERSID	COST PER
WEAPON	P^h	P^k	LETHALIT	MAX	MIN	CUTOU			
Penguin (SH-60)	0.6	0.8	0.5	Y	Y	N	HELO	N	CLASSIFIE
Harpoon	0.3	0.8	0.	Y	Y	N	PWR/TARGETI	N	$474,609
SM-1/2	0.2	0.7	0.	Y	Y	Y/N	POWER/RADA	N	$400,000
RAM	0.2	0.6	0.1	Y	CLASSIFIE	Y	POWER	N	$393,103
NSSM	0.6	0.6	0.	Y	N	Y	POWER	N	$165,400
CIWS (1B)	0.8	0.9	0.7	N	N	Y	POWER/AIR	LIMITE	NEGLIGIBI
3-inch / 5-inch Gun	0.3	0.8	0.2	N	N	Y	POWER/RADA	N	NEGLIGIBI
Machine Guns	0.2	0.2	0.0	N	N	Y/N	NONE	Y	NEGLIGIBI
Small Arms	0.0	0.0	0.0	N	N	N	NONE	Y	NEGLIGIBI
Javelin	0.9	0.9	0.8	N	N	N	NONE	Y	$65,000

Table 1. LT. Cobian's Relative Comparison of Weapon Systems (Cobian, 2002).

Additionally, he showed the ineffectiveness of shipboard weapons employed today at preventing a small boat swarm attack. The results are disheartening, especially since the next best weapon system at prosecuting an attack was the Close-In Weapon System (CIWS), which requires shipboard power and interlocks controlled by the Commanding Officer (CO) to be disabled prior to use. The original purpose of the CIWS is for ship defense from sea-skimming anti-ship missiles. Recent modifications have been made to help broaden its use against low elevation fliers such as helicopters and surface threats, but these features require operator control, and do not utilize the automated features of CIWS. Additionally, there may be restrictions on both radar emissions or gun traversing while entering or staying in port, both of which limit the CIWS' effectiveness. LT. Cobian's work showed the dangerously vulnerable state warships are placed in when pulling into port, not just from its weapon limitations, but due to its proximity to land. Warships when in port are limited in their ability to maneuver due to traffic or shoal water. Given the ease at which a swarm can hide in a port, a ship is definitely in a disadvantageous situation.

Apart from the pier-side situation that the USS Cole faced in Yemen, swarm attacks at sea are also of great concern. Abel's (2009) work on analyzing frigate defensive effectiveness showed that in the green water environment, speed and maneuverability can be just as effective as having enhanced weapon systems at preventing a successful swarm attack. Increasing the speed of his modeled Fast Frigate with Helicopter (FFH) allowed it to outmaneuver and outrun swarming SFACs. This conclusion correlates with some established naval doctrine concerning small boat attacks. The stiff-arm tactic, for example, consists of accelerating to full speed toward open-ocean while engaging crew-served weapons on pursuing SFACs. The reason behind this is that small boats are more susceptible to ocean sea states, and are hindered in aiming ordinance at an avoiding vessel. If everything goes well, the SFACs may break off the attack and return to their base of operations or be rendered inoperable.

Figure 3. Photo of Iran’s Great Prophet 5 Small Boat Exercise

Utilizing evasive maneuvers and tactics can have significant results when avoiding the small boat attack, be it armed assault or piracy as outlined in Lieutenant Commander (LCDR) William Major’s article on assessing counter-piracy tactics. Here LCDR Major showed an increase in effectiveness of 36% of avoiding a successful piracy boarding by commercial ships employing evasion maneuvers alone (Major, 2012).

While enhancing the ship’s capabilities and weapons are obvious routes to improve naval ship survivability in the small boat swarm environment, including a shipboard helicopter further increases that effectiveness. While Kapitanleutnant Abel’s work did investigate the benefits of shipboard helicopters, Turkish Navy Lieutenant Junior Grade (LTJG) Omur Ozdemir explored the capabilities of several variants of surface combatants. In his study, he found that the U.S. Navy's new LCS class of ships performed very well due to its capability of carrying two armed helicopters. This feature, in a non-Surface to Air Missile (SAM) environment, allowed his modeled LCS ships to detect and engage the SFAC threat far earlier (Ozdemir, 2009). This allowance of time is vital since it can allow the ship to plan and prepare for an attack, which is the antithesis to the swarming strategy. Surprise and mobility are the cornerstones of the swarm attack, as outlined in Iran's Doctrine of Asymmetric Warfare (Haghshenass, 2006). Therefore, a possible way to combat the swarming threat is early detection, which is greatly enhanced when patrolling aircraft are employed.

D. AGENT BASED MODELING

With the propagation of widespread computers and computational resources, the concept of agent based modeling has seen a boom in popularity over the past two decades. Their applications are extensive, with examples ranging from observing financial market behaviors to agents conducting counter terrorism operations in modeled environments. Their origins can be traced back to the 1940s with the Von Neumann Machine which consisted of a theoretical machine that would replicate itself based on a prescribed series of processes. While it is a far cry from the modeling software used today, it created the basis for simulation modeling. It is still hard to identify the first time that the phrase "agent based" modeling was created, but some sources indicate that the term was coined by John Miller's and John Holland's work "Artificial Adaptive Agents in Economic Theory" (Miller and Holland, 1991)

One of the most notable studies conducted in early agent based modeling was Craig Reynold's, "Flocks, Herds, and Schools: A Distributed Behavioral Model." This work focused on the establishment of modeled entities, called boids, which were programmed with set behavioral urges with regards to the other boids around them. First was the desire to stay near the center of the flock, which in general, means boids want to fly near other boids. The second was collision avoidance, in that boids did not want to come into contact with nearby boids and other obstacles. Finally, the urge to match speed with other boids was instilled in the entities. This would create three separate signals in a three dimensional vector space trying to dictate boid flight paths. The boid navigational module would receive these inputs, and try to generate an optimized path to follow based on these signals and their associated weighting factors.

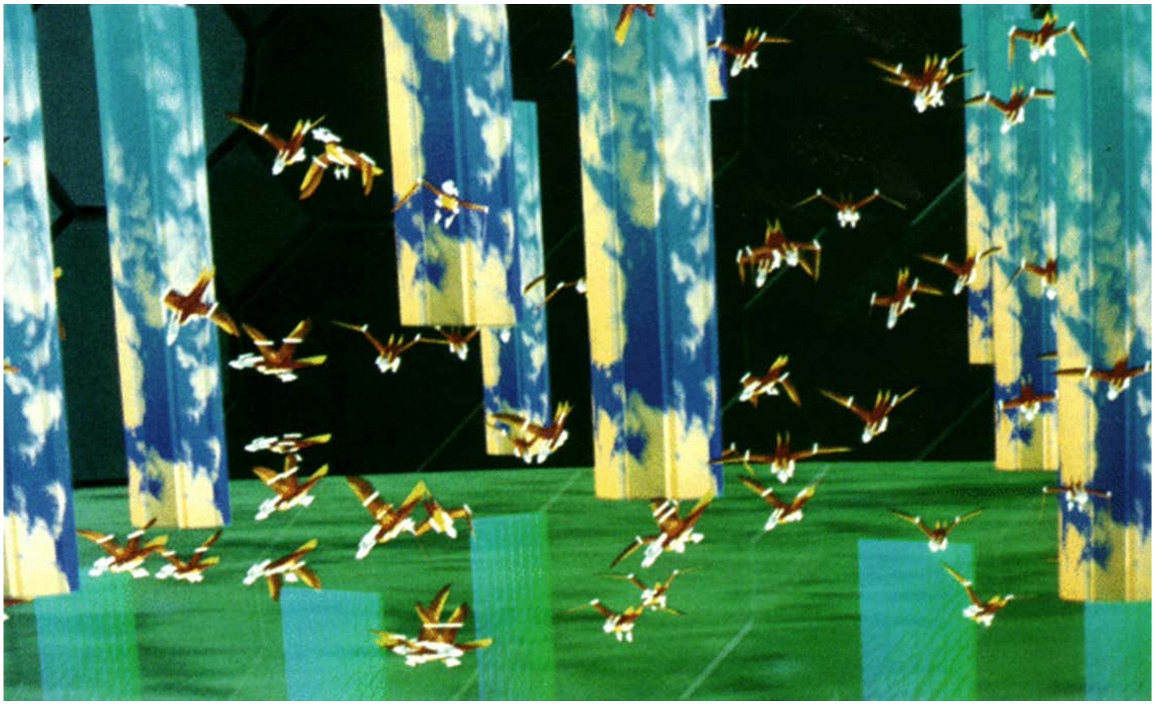

Figure 4. Graphical Simulation of Boids in Flight

This work was one of the first attempts to model behavioral responses by simulated agents since not only did they react to themselves, they also reacted to their environment when obstacles were placed in their path. This modeling effort led to much of the work produced today since the real essence of agent based modeling is trying to identify emergent behavior which can lead to new and unexpected answers.

The notion of behavioral response in agent based modeling was addressed in Macy and Willer (2002). They were trying to understand the sociological influences in an agent based modeling environment and the discovery of emergent behavior of agents placed in differing sociologic situations. While agent based models don't necessary aim to give specific results to a study, they do try to gain further understanding of the processes that may appear. Unlike Craig Reynold's work which focused on the response of a single boid as it flew in its flock, the work performed by Macy and Willer was to understand how the different social networks involved impacted the social behavior of the agents. When discussing emergent order and relational stability they address how, in the Prisoner's Dilemma, the optimal choice for an individual play is defection. This choice does not hold up however when repeated play and relationships are introduced. At this point, it was impossible to predict the outcome of the game because the social behaviors of the agents influence the choice of when to defect or cooperate. Ultimately the Tit-for-Tat strategy proved to be the most advantageous since it always cooperated until it was betrayed, but responded to betrayal with one time betrayal followed by forgiveness. At the end of their study, they concluded that agent based models presented an extensive field of study for sociologists given its behavioral study applications.

E. DESIGN OF EXPERIMENTS

As previously mentioned, the OSN data collection effort for their study involved utilizing factorial designs. While factorial designs are definitely useful for simulation experiments, when the number of factors increases, or the number of levels for a particular factor increase, then more efficient designs may be required. In Sanchez and Wan (2009) they show how quickly both course and fine factorial designs become cumbersome and computationally expensive as more factors or levels are introduced. Since factorial designs produce situations of exponential growth in data requirements as the number of factors increase, their use has to be limited to experiments with low numbers of factors. Their solution to this computational growth problem is the use of design strategies such as Central Composites and Nearly Orthogonal Latin Hypercubes (NOLH). Both of these strategies attempt to establish a space-filling design that provides insight onto the multidimensional space of an experiment which may have been too large for a factorial design. The NOLH utilized in the data collection process of this thesis is the current evolution of a number of previous works concerning DOE. Cioppa (2002), Hernandez (2008), and Vieira et al. (2011) formed the current practices in DOE, particularly Nearly Orthogonal Latin Hypercubes and space filling designs.

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III. METHODOLOGY

A. INTRODUCTION

It is important to first clarify that the processes for attaining the baseline model and advanced models are different, and the questions that they are intended to answer are also dissimilar. The baseline model approach gains its importance by establishing a basis for comparison between the provided OSN model and the NPS MANA generated model. This is accomplished by analyzing the outputs of each of the models, and showing through regression that the models are very similar, to the point of interchangeability. The advanced model approach expands upon the baseline model design to increase the analyzed space to try and answer the research questions presented. Initially this focus is to stress the baseline model by increasing opposition strength and behavior, and observing friendly force response. The following portion of the advanced models is to provide a similar increase in friendly force capabilities, and analyzing whether outcomes remain similar to the baseline study, or if other operational factors become more significant.

B. BASELINE MODELS

As described above, the baseline study is as attempt to generate an agent based model in MANA that accurately reflects the OSN C++ agent based model. This model is very simple, and it is intended to be this way in order to initially identify important factors of the OPV prior to the introduction of noise variables.

Why use MANA? Nothing in this thesis is intended to state that MANA is a superior agent based modeling software to others that are currently in the simulation market. Its use is specific to its availability and its compatibility with the resources present at the Naval Postgraduate School and the SEED Center. That being established, MANA does provide capabilities that were easily tailored to reflect the factors present in the OSN model. Factors like range and P_{hit} probability plots and agent dependent factors could be directly implemented in MANA with little effort. In addition to agent factors, replication of the battle space in MANA was straight forward using parameters provided from the OSN scenario descriptions.

1. OSN ASUW Scenario Description

The OSN model is a battle space 60 nautical miles wide and 100 nautical miles long. A simple Cartesian coordinate system is used to establish agent location. In this scenario, the top left corner of the battle space is represented by the (0,0) point, and the bottom right represented by (60,100). There are two types of agents in this battle space, the OPVs and the SFACs. There are a total of 12 agents initially on each model run, three OPVs and nine SFACs. There is one additional agent, which is introduced by a varying factor dictating the presence of a helicopter in support of the OPVs.

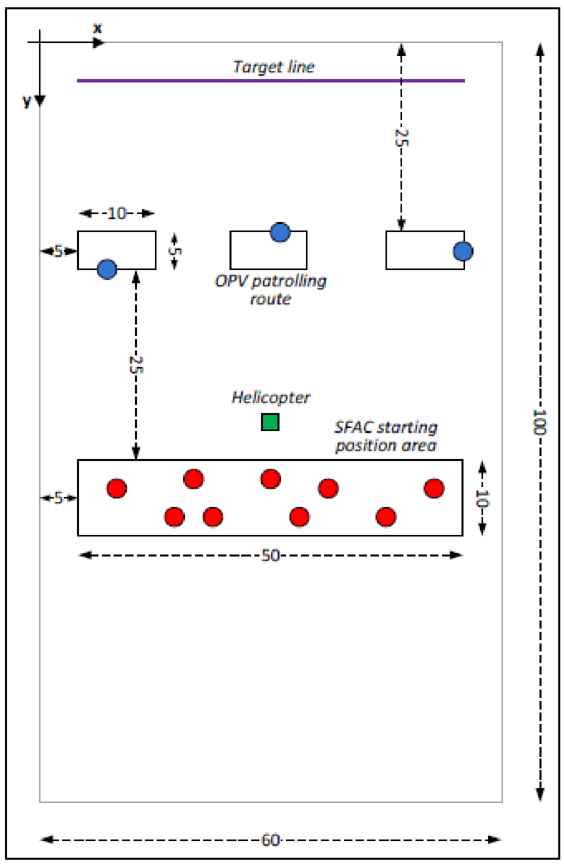

Figure 5. OSN Scenario Map

Referencing Figure 3, the OPVs begin model runs at the following starting locations:

- OPV 1: (5,25)
- OPV 2: (25,25)
- OPV 3: (45,25).

OPVs, once generated, begin by patrolling an established route in defense of a 50 nautical mile long goal line located at (5,5) and extending to (55,5). The patrol route for each OPV is listed below:

- OPV 1 patrol route: (15,25), (15,30), (5,30), (5,25)
- OPV 2 patrol route: (35,25), (35,30), (25,30), (25,25)
- OPV 3 patrol route: (55,25), (55,30), (45,30), (45,25).

The nine SFACs are generated in a 50 nautical mile long by 10 nautical mile wide homebox with coordinates:

- SFAC Homebox: (5,55), (55,55), (55,65), (5,65).

Their placement is random, and once generated, they proceed directly toward the goal line with the shortest route possible. They do not deviate from this course, regardless of the presence of the OPVs.

The helicopter agent, if present, is generated at (30,50), and provides detection and classification data perfectly to the OPVs.

OPVs patrol their prescribed waypoint list at a set speed of 15 knots in the absence of detected SFACs or SFAC relayed data from other OPVs or the helicopter. If SFACs are detected, a target list is generated, and SFAC targets are distributed to the OPVs by a decision algorithm, assigning at most three SFACs to each OPV. This algorithm attempts to assign SFAC targets to the closest available OPV. Once target data is received by the OPV, be it organic or inorganic, the OPV accelerates to maximum speed and attempt to intercept and prosecute the SFAC. OPV weapon priority is its four available missiles, followed by a naval gun if equipped. OPV weapon specifics are detailed below. If an OPV destroys all three of its assigned SFACs, it disengages and proceeds back to its patrol route. These successful OPVs attempt to kill further SFACs passing within range if they still have ammunition available, but they do not maneuver to intercept. Mission success for the OPVs is the successful defense of the goal line, or in other words, the successful elimination of all nine SFACs. The simulation ends if OPVs achieve mission success, or if a SFAC reaches the goal line.

a. Model Factors

The seven factors in the OSN model are SFAC Type, OPV Missile Type, OPV Gun Present, Helo Present, OPV Max Speed, OPV Mast Height, OPV Length at Waterline.

- SFAC Type – A binary factor of Type 1 SFAC or Type 2 SFAC, which adjusts the SFAC maximum speed and size. Type 1 SFACs have a maximum speed of 25 knots and are 7 meters tall. Type 2 SFACs have a maximum speed of 36 knots and are 10 meters tall.
- OPV Missile Type – A binary factor of missile Type 1, the Marte missile system, or Type 2, the Exocet Missile system.

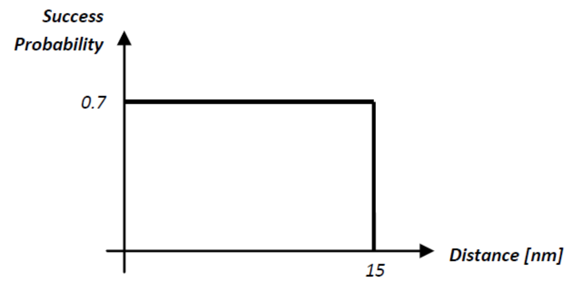

Figure 6. Marte Missile P_{hit} – Range Profile

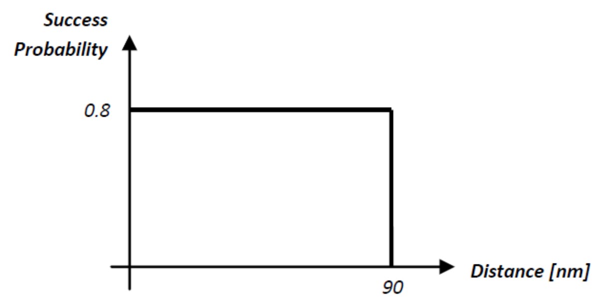

Figure 7. Exocet Missile P_{hit} – Range Profile

- OPV Gun Present – A binary factor describing the presence of a naval gun on the OPV. In the OSN data, this factor has values of either 0 or 3, with three representing the gun is present. The gun has three shots of ammo with the below P_{hit} distribution:

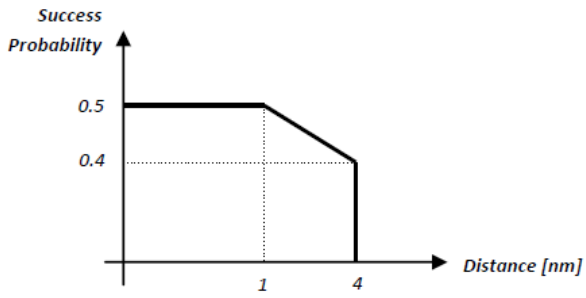

Figure 8. Gun P_{hit} – Range Profile

- OPV Max Speed – A continuous factor, with a range of 22 knots to 40 knots with 2 knot increments, describes the speed an OPV accelerates to when it detects and is prosecuting a threat.
- OPV Mast Height – A continuous factor, with values of 13, 16, 19, and 22 meters, which describes the height of the equipped radar system on the OPV. This factor, in tandem with the type of SFAC, determines the detection and classification range of the OPV. For the baseline scenario, the detection range and classification range are the same.
- OPV Length at Waterline – A continuous factor, with values of 50, 65, and 80 meters, which influences the turn rate and speed of the OPV.
- Helo Present – A binary factor of 0 or 1 which describes if the helicopter agent is present in the scenario.

b. Factorial Design

To explore all possible data points in the design space, the OSN model used a full factorial design. To replicate every data point provided by the OSN design and the associated data could be computationally expensive given that there are seven factors in the model, some of which are not binary. Additionally the MOE of the OSN model is the percentage of time the OPV successfully defended the goal line. This percentage is to the first decimal place, which implies each data point relating to a specific set of model factor values was run with at least a thousand replications. Given that the data set contains roughly 1900 data points, the full factorial would require almost two million model runs.

2. MANA Model Differences

While many of the specific factors and their associated ranges could be entered directly into MANA, there were some that could not, or required modeling finesse.

a. SFAC Homebox

While the dimensions of the homebox could be accurately modeled in the MANA environment, the behavior of agents generated in the box created issues that had to be addressed. In the OSN model, SFACs would be randomly generated in the homebox and proceed directly north to the goal line at best speed. MANA's homebox generates SFACs in the same manner, but agent movement is directed by an influence system. This influence system helps to prioritize agent behavior in a model run as the modeler dictates. For the SFACs, that behavior is set at 100% influence to proceed to the first waypoint, which was placed in the same location as the goal line of the scenario. The issue that arises is that MANA only permits a series of waypoints for a single homebox, not a goal line. Therefore, SFACs generated in one large box would all converge on a single point placed on the goal line, which was the first waypoint. This behavior is undesirable since it would impact the importance of the OPV patrolling near the assigned waypoint. To overcome this problem, the single large homebox as described in the scenario was divided into 21 smaller, equally sized homeboxes associated with the SFAC squad. Each small homebox had its assigned waypoint directly north from its location, creating a line of waypoints. This series of 21 waypoints form the goal line in the MANA environment. To ensure that the SFAC agents would be generated in the same manner as in the single larger homebox, a size proportionality option was used. This feature makes the probability of having a SFAC generated in a particular homebox be proportional to the box' size. Since each box is equal in size, then each box has the same probability to generate every SFAC that is introduced to the scenario. Since there are nine SFAC agents, not every box would generate an agent, additionally some homeboxes may generate more than one agent. This allowed for the same behavior as a single large homebox as in the OSN model.

b. Missile Speed

While the OSN model introduces a set missile velocity of 300 meters per second, MANA is not able to introduce this feature. Since missile speed is present in the OSN model, a delay is introduced from missile launch to missile hit on a targeted SFAC. This delay inhibits the OSN OPVs from launching another missile until the outcome can be determined from the previous launch. If the missile hits, the OPV retargets a different SFAC and prosecutes it. If it missed, the OPV fires another missile and repeat the process. In MANA, the missile launch and P_{hit} determination occur essentially instantaneously, so the only difference between the two models is the delay in time associated with missile launches. This delay however is insignificant in simulation outcomes, as shown in the analysis portion of this thesis.

c. OPV Length at Waterline

In real world environments and ship synthesis considerations, ship length at waterline is an important factor since it impacts speed, turn rate, stability, and space considerations. In an operational modeling environment however, that impact may or may not be significant. In the OSN model, OPV length is placed as a varying factor. MANA, however, cannot replicate this feature specifically, yet it can simulate inertia of individual agents. Values for this inertia factor can be added to force OPV agents to behave like naval vessels, but there does not exist a direct way to compare the 50, 65, and 80 meter factor set points for the OSN model to specific inertia values entered into MANA. This inertia value is set to 15 in the model runs, since it is stated that values above 10 begin to approach ship behaviors. This accounts for turn and speed impacts for the OPVs in the scenario. For the space considerations, length at waterline may impact gun and missile launcher placement, and create firing arc cutouts, which are ranges where the weapons cannot fire since they would risk striking the own ship’s superstructure. It is not stated if cutouts are present in the OSN scenario, therefore the length at waterline factor only affects maneuverability of the OPVs. This impact however is shown to be insignificant in the analysis section.

d. Contact Prosecution

As mentioned in the scenario description, contacts detected by OPV and helicopter sensors are added to a contact list which is in turn divided amongst the OPVs for prosecution. MANA does not behave in this fashion when groups of agents are targeted by other groups of agents. Agent prosecution is handled by the focusing of movements and forces to the geographical center of gravity (COG) of opponent agents. For the MANA baseline model, this means that OPVs maneuver themselves towards a varying point near the center of all detected SFACs. This point shifts continuously, influenced by newly detected, lost, or destroyed SFAC agents. A problem arises when a single outlier SFAC is generated in one of the extreme left or right homeboxes, and the rest are grouped on the opposite side of the environment. OPVs move toward the cluster of SFACs since the COG is centered near them, while the outlier may be able to proceed to the goal line unmolested. While not intended, this issue is permitted since it may be a tactic actually employed by real life agents attempting to bypass an established defended perimeter.

When addressing the established SFAC prosecution list from the OSN model, MANA agents generally engage the nearest possible target. However, MANA agents can be provided with a list of target priorities to prosecute in order, but this feature must be done prior to model runs, and cannot be randomly generated. Also, the modeler can chose to allow or limit agents to attack their nearest threat with specific weapons, and reevaluate their targets as they are eliminated. This feature was used in the MANA baseline model, so OPVs prosecute the nearest detected SFACs first with missiles, and then work out towards further contacts.

e. OPV Max Speed

In the OSN model scenario OPV max speed, while a continuous factor, is modeled with integer levels between 22 to 40 knots increasing in two knot increments. Speed is a continuous factor, however, and it is feasible that insightful information can be drawn from speeds allowable within the OSN established levels. Therefore, the DOE utilized in the modeling process of this thesis evaluates speed at levels over the continuous spectrum between the high and low setpoints.

f. OPV Mast Height

Similar to the previous argument concerning OPV max speed, OPV mast height can theoretically exist at values between the low and high set points of 13 and 22 meters in the OSN model. This being the case, OPV mast height was modeled as continuous in same manner as OPV max speed.

g. Design of Experiments

While the computational resources present at NPS are substantial, the number of simulation runs to replicate the full factorial is excessive given that there are techniques available to gain insight on the multidimensional space with far fewer data points. The technique which was employed is a space filling design that drastically reduces the amount of required computational work while still generating samples spanning the range of the full factorial. To accomplish this, a space filling design of two hundred different data points for the baseline study was used. This design covers roughly twenty percent of all possible data points and each individual data point has a thousand replications performed to generate a percent success of OPV goal line defense.

3. Limitations and Assumptions

a. Limitations

1) I was limited in my ability to directly replicate the OSN model since it was written in the C++ computer programming language. I am inexperienced in this computer language, and I do not have sufficient time to learn it and rewrite my own code to produce a model that behaves similarly to the OSN model.

2) I was limited in the area of computer replication time since the OSN design of experiments explored the full factorial approach to data collection. To perform

the necessary number of runs to achieve the full factorial, it would place undue strain on highly valuable computational resources of the SEED Center.

b. General Assumptions

1) To account for Limitation #1, I have assumed that MANA is an adequate agent base modeling software, and that it can perform in similar fashion as the OSN model if I utilize it proficiently.

2) To account for Limitation #2, I have used a space filling design that is superior to the full factorial in terms of both efficiency and coverage of the factor space.

C. ADVANCED MODELS

The intent of the advanced scenarios is to try and identify any change or emergence of factor importance that are not visible in the baseline models. The process is a two-step approach, in that initially, the SFACs of the baseline studies are enhanced with behavioral features capable in MANA. These behavioral enhancements are Avoidance and Aggression. For Avoidance, SFACs attempt to evade and out-maneuver the OPVs while attempting to reach the goal line. In the Aggression scenarios, SFACs attack detected OPVs utilizing suicide weaponry capable of eliminating the OPVs from the battlefield. Additionally, a third scenario consisting of a combination of Avoidance and Aggression SFACs are implemented to stress the OPVs. Each scenario is run with the OPVs generated during the baseline study to evaluate their ability to counter a more robust threat. Once these three models are run, another set of analyses are conducted utilizing enhanced OPVs with capabilities established in Abel (2009), Ozdemir (2009), and Cobian (2002). These improved OPVs are placed in the same scenarios described previously to see if any emergent behavior or dissimilar outcomes appear. For each of the advanced scenarios, the number of SFACs has been increased from nine to eighteen agents to help focus the performance of the OPVs on their associated weapons and capabilities.

1. SFAC Avoidance vs. Baseline Scenario

As mentioned in the baseline description of the scenarios, MANA utilizes a system of influences to help direct agent motion in the simulated environment. In the baseline scenario, the SFAC agent's only priority was to reach the goal line using the shortest route from their spawn location. This influence has been altered by introducing a detection capability in the SFAC agents comparable to the OPVs'. With this capability, SFACs both see and identify approaching OPVs as a threat and attempt to avoid them, while at the same time, attempting to reach the goal line.

Given the small nature of the SFAC in relation to sea state inherent to open ocean conditions, a stealth feature available in MANA has been activated for the small boat agents. This stealth set-point is established at 70% effectiveness. What this means is that for any individual sweep of radar, there is a 30% chance to detect the SFAC. While a disadvantage for a single scanner, the tactical sharing of target information between OPVs allows for areas of coverage being swept by multiple radars, thus increasing probability of detection. The resulting effect is that when SFACs are more distant to OPVs and outside multiple radar sweep areas, they are harder to see. However, detection improves as OPV and SFAC separation decreases. This decrease in visibility as a small object gets further from an observer is more realistic in nature, and coincides with operational experience.

Aside from the above modifications to the MANA model, no other changes have been made to the baseline model. This effort is to try and identify if factor significance is altered by SFAC motion and avoidance.

2. SFAC Aggressive vs. Baseline Scenario

Along with the detection and stealth capabilities applied to the SFAC agents in the Avoidance scenario, SFACs in the Aggressive scenario were enhanced with suicide weaponry capable of destroying the patrolling OPVs. The influence system for this scenario has been reversed when SFACs detect OPVs. Instead of fleeing from approaching OPVs, SFACs close and attempt to collide with the OPVs to try and destroy them. This tactic has some historical credence since it was utilized during the Sri Lankan

Civil War by the Tamil Sea Tigers in order to cripple and demoralize Sri Lankan naval forces.

3. SFAC Combination vs. Baseline Scenario

The Combination scenario is a blend of both the Avoidance and Aggressive scenarios. Half of the SFAC agents follow the Avoidance strategy, while the other half follow the Aggressive mindset. The goal of this scenario is to identify if Aggressive behaving SFACs influence the OPVs' capability in intercepting them, and the Avoidance SFACs.

4. OPV Enhancements

The characteristics of the OPVs have been altered for the next three scenario runs in an effort to introduce more realism to the modeling environment. While the effectiveness of the equipped Marte and Exocet missile systems has gone unaltered, the gun mount has been significantly changed to better reflect actual naval gun characteristics. Additionally, naval ships currently being designed and produced have begun the employment of new weapons systems aimed at countering the small boat swarm threat. The Griffin missile system is one such weapon, given its employment on the U.S. Navy's new LCS ships. While the weapon system is still undergoing testing, the addition of this weapon acknowledges the significance of the small boat threat. Finally, a behavioral enhancement for OPVs has been implemented to help maintain adequate separation distances between approaching SFAC agents. This behavior is intended to parallel current close approach and collision avoidance situations practiced by warships at sea today.

a. Naval Gun

In the baseline scenario, prescribed gun P_{hit} effectiveness was 0.5 for targets within one nautical mile, decreasing linearly to 0.4 for contacts within four nautical miles. This weapon effectiveness is unrealistic when referencing historical records of naval gunfire in wartime environments. As an example, of the 531 U.S. PT boats used in WWII by the U.S. Navy, only seven of the total 99 lost were due to enemy naval gunfire (Bulkley, 1962). This equates to a P_{hit} of 0.0132, and this value is non-range specific, which means the seven PT boats destroyed by naval gunfire could have been destroyed at far range or when close aboard their adversaries. This low P_{hit} also correlates with gunfire effectiveness seen at the Battle of the Falklands on December 8, 1914 where British estimates put gun hit accuracy near 1%. This engagement took place between large, slow moving warships equipped with 12” guns, not small and agile fast boats moving in excess of 30 knots. While it can be argued that naval fire-control technology is far more advanced than WWI and WWII systems, the speed and agility of modern day SFACs are significantly higher than comparable boats of that era. Ultimately, professional experience and historical records help to dictate probability of hit characteristics far lower than those provided by the OSN baseline model.

Developed in 1964 by the Italian weapon manufacturer, Oto Melara, the 76mm Otobreda naval gun is one of the most successful and widely used naval guns in the world today.

Figure 9. 76mm/62 Caliber Otobreda Naval Gun

Used in 53 navies worldwide, this gun is capable of firing 27lb projectiles at a rate of 85 rounds per minute with a maximum range of 20 kilometers. Mounted on many frigate class ships, such as the U.S. Navy’s Oliver Hazard Perry class, this gun is also compact enough to be mounted on smaller corvette and OPV class ships. Given its country of origin, compatibility, and extent of proliferation, the 76mm Otobreda has been chosen to be modeled in the enhanced OPV model runs.

i. Model Specifics

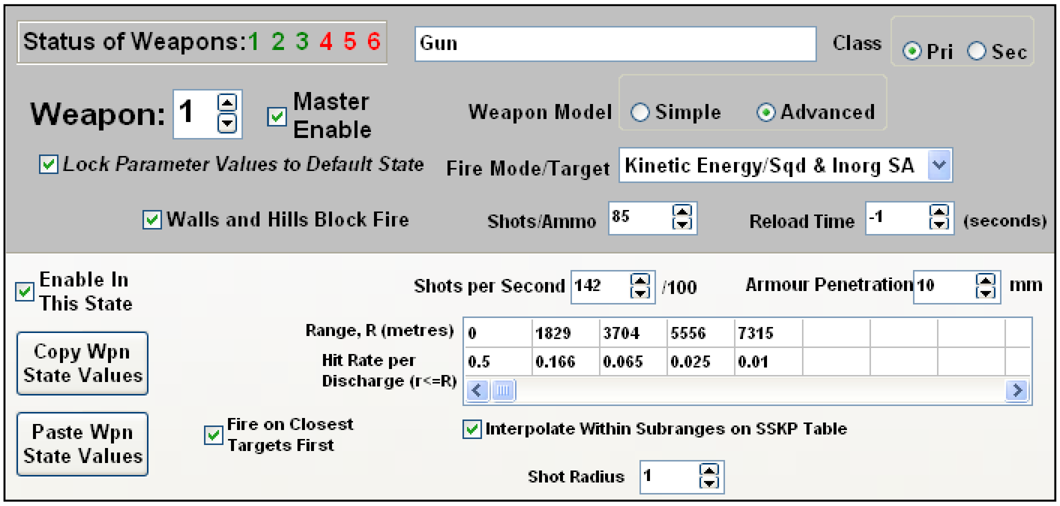

Figure 10. Screenshot of MANA Naval Gun Characteristics

The characteristics of the naval gun equipped on OPVs in the enhanced model runs are detailed in Figure 12. While the probability of hit at or near point blank range is still a modest 50%, the decrease in gun hit effectiveness falls off exponentially to 1% at four nautical miles. While it may be argued that even this level of effectiveness is still too optimistic given the nature of small boat engagement, without the availability of actual naval gunfire effectiveness data in small boat attacks, this assumption seems much more reasonable that the previously prescribed gun hit profiles in the baseline models.

Additionally, the ammunition considerations of the baseline model have been altered to a more realistic value. In the prior models, OPVs were allowed three engagements with approaching SFACs with the equipped gun. This does not coincide with typical ammunition load-outs of warships at sea. The 76mm Otobreda naval gun, for instance, contains one full minute’s worth of ammunition in the gun magazine, or in other words, 85 shells. This amount of ammunition is assumed sufficient for the modeled engagements since there would not be adequate time available to reload an expended magazine prior to the completion of a simulated run.

b. Griffin Missile System

Given the recent investment of advanced weapons to combat the small boat swarm threat, the U.S. Navy's LCS program gives credence to the severity of the SFAC threat. Partly as a counter to published Iranian naval warfare doctrine, and its reliance on small boat swarms, the U.S. has contracted the weapons manufacturing company, Raytheon, to help combat the growing problem. Their answer is the Griffin Missile System.

Figure 11. Raytheon Griffin Missile Test Launch

Originating from Ratheon's Rolling Airframe Missile (RAM), the Griffin is a smaller, less expensive weapon designed to engage close range surface threats. With engagement ranges of only a few miles, the Griffin is slotted as a defensive weapon, employed in tandem with other shipboard defensive systems such as the CIWS, crew served weapons, and the naval gun. On June 15, 2012, the U.S. Navy engaged three SFAC targets on a sea-based platform with three laser guided Griffin missiles, each scoring direct hits (Paris, 2012). While the specifics of the Griffin hit and kill probabilities are currently unknown, previous weapon systems such as the Hellfire and

RAM missiles have proven to possess very high P_{hit} probabilities. The specifics of the MANA modeled Griffin missile system is shown in Figure 14 below.

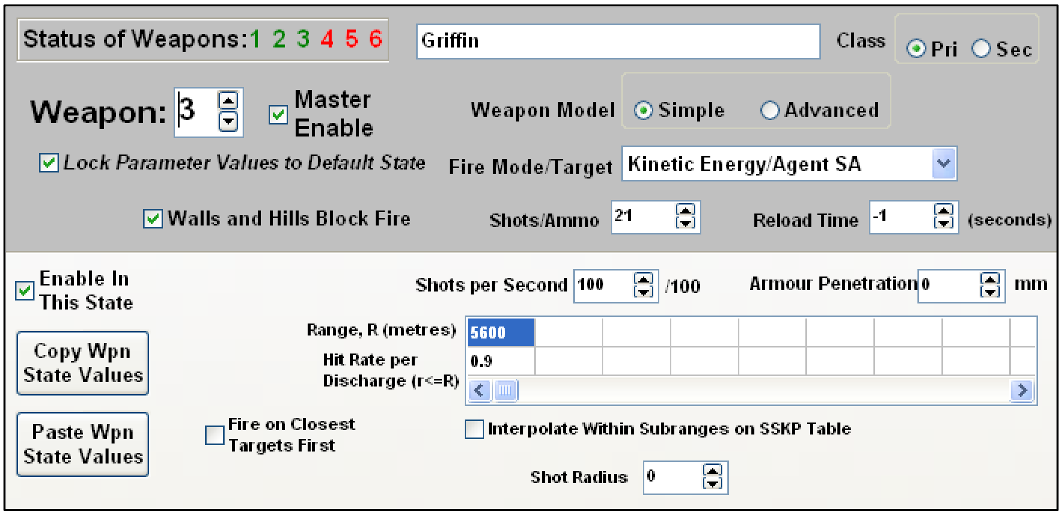

Figure 12. Screenshot of MANA Griffin Missile Characteristics

While the number of missiles loaded on naval Griffin launchers is unknown, since the missile heralds its origins from the RAM system employed on naval warships for air defense it is assumed that the Griffin holds a number of missiles per launcher comparable to the RAM. This ultimately creates a very effective, short range defensive weapon system to combat the small boat swarm threat.

c. Risk of Collision Situations

U.S. naval warships operating on the oceans today do so by adhering to a strict set of instructions put forth by their commanding officers (CO). These instructions range from permission items to subordinate officers onboard, to rules and expectations of key watch-stations performing their routine duties. One such document readily known to most surface warfare officers (SWO) is the CO's Standing Orders (CSO). The CSO is evaluated and produced by every CO upon their arrival to a new command, and it dictates how watch-teams conduct their watches at key locations, such as the Bridge, Combat Information Center (CIC), and Central Control Station (CCS). For the bridge team, safe maneuvering of the ship is of principle importance, and the most serious of situations for the bridge team to face is the Risk of Collision (ROC) situation. Collision at sea is a serious problem, not only because it's an embarrassment for the CO. It damages the ship, injures crew, and possibly impacts the environment. Given its severity many COs detail their expectations to the bridge in regards to ROC, usually involving CO notification, statements of intention to the involved vessels, and avoidance. The avoidance portion of ROC is important for this study since in the previous Aggressive scenario, OPVs would not attempt to avoid approaching SFACs laden with explosives. This resulted in the loss of OPVs which may have been able to avoid and defend themselves from SFAC attack, and thus continue to defend the objective. From operation experience, avoiding ROC can take place at any range, but generally ship course alterations become more drastic as distance and time to collision decreases. In the enhanced OPV MANA runs, an extreme ROC situation is deemed to exist when SFACs encroach within two nautical miles. Once this distance is violated by attacking SFACs, OPVs attempt to avoid and steam away from threats as quickly as possible. At this point, OPVs continue to eliminate the pursuing threat as best as possible, and only return to previous operations when all SFACs are removed from the two nautical mile radius.

D. MODEL REPLICATION DISTRIBUTION

As previously mentioned, the baseline MANA model consisted of 200 distinct data points, with one thousand runs per point. This resulted in 200 rows of averaged data, producing a MOE comparable to the OSN baseline data. For the advanced model runs, the number of replications is significantly reduced, since it is the effort of the baseline model to establish interchangeability between the OSN and MANA baseline models. With this interchangeability established, it can be presumed that if the capabilities present in the advanced MANA models were available in the OSN modeling environment, that it would produce similar results. Below is the distribution of model runs for the advanced MANA models.

- Advanced Model (Avoidance Scenario) – 200 data points, with 50 replications per data point
- Advanced Model (Aggressive Scenario) – 200 data points, with 50 replications per data point
- Advanced Model (Combination Scenario) – 200 data points, with 50 replications per data point

- Enhanced OPV Model (Avoidance Scenario) – 200 data points, with 50 replications per data point
- Enhanced OPV Model (Aggressive Scenario) – 200 data points, with 50 replications per data point
- Enhanced OPV Model (Combination Scenario) – 200 data points, with 50 replications per data point

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IV. ANALYSIS

A. INTRODUCTION

The prior three chapters have shed light onto the initial situation, historical influence, and steps taken to develop the models necessary to answer the research questions. This chapter shows the analysis techniques and tools utilized to scrutinize the data for insightful information. After this overview, an in-depth analysis of the produced data was conducted between the baseline and advanced model datasets.

Initial analysis efforts focus on model interpretation and interchangeability between the OSN and MANA models. Additionally, this analysis results in the determination of factor importance in the baseline scenarios. These results are important because they establish the basis which the advanced model factors are compared against.

The analysis of the advanced models consists of two phases, first being focused on the impact of SFAC improvements and behaviors on the baseline modeled OPVs. It is the goal of this portion of the study to understand the impact of the increased capabilities allowable in MANA. Secondly, this work addresses the enhancement of the OPVs, and how the introduction of more realistic capabilities of a warship compare to the improved SFAC problem. It is from this point that the following conclusions and results are based upon.

B. ANALYSIS TOOLS AND METHODS

Before any useful information can be pulled from the raw data, an inspection needs to be conducted to identify any errors or data corruption. After this inspection, the data then needs to be molded into a form that can be fed into an analysis tool. The analysis tool utilized in this analysis is JMP 9 Pro due to its insightful visual outputs as well as its ease of use in drawing out constructive output.

1. Data Inspection

a. Baseline Model Data

As mentioned in the first chapter, the OSN data set consists of 1921 rows of data with a response as a percentage chance of successful defense, taken to the first decimal place. The OSN model explores the full factorial, which means every possible combination of factor settings has been investigated thus creating a complete representation of the entire multidimensional space. A sample of the OSN data is shown in Table 2.

GUN	HELO	LWL	Max Speed	MastH	SFAC	SSM	MOE
0	0	50	22	13	1	1	11.2
0	0	50	22	16	1	1	12.4
0	0	50	22	19	1	1	13.2
0	0	50	22	22	1	1	16.8
0	0	50	24	13	1	1	10
0	0	50	24	16	1	1	13.6
0	0	50	24	19	1	1	14.8
0	0	50	24	22	1	1	17.8
0	0	50	26	13	1	1	10
0	0	50	26	16	1	1	15.2

Table 2. Portion of OSN Dataset

As mentioned in the Methodology chapter, Table 2 shows all seven factors being analyzed and a portion of the factor levels.

The data generated from the baseline MANA model consisted of two hundred data points, utilizing a space filling design as detailed earlier. Each data point was simulated one thousand times to generate a mean response comparable to the OSN data set. A sample of the averaged baseline MANA data is shown in Table 3.

8/0 Cols	GUN	HELO	Max Speed	MastH	SFAC	SSM	MOE
1	0	0	23.628141	16	2	2	41.3
2	0	1	39.909548	19	1	1	34
3	3	0	37.557789	13	1	2	94.1
4	0	0	25.708543	22	2	2	50.9
5	3	1	34.482412	13	1	1	84.3
6	0	1	34.753769	13	1	2	54.4
7	3	1	31.407035	13	2	1	73
8	0	0	30.140704	13	1	1	18
9	0	1	27.427136	16	2	2	45.6
10	3	0	30.592965	16	1	2	95.9
11	0	0	32.854271	16	2	2	42.9
12	0	0	29.507538	22	1	1	23.1

Table 3. Portion of MANA Baseline Dataset

As explained in the Methodology portion, the baseline data generated from the MANA model does not contain the Length at Waterline (LWL) factor that is present in the OSN model. The data are also averaged to generate the percentage MOE shown in the seventh column. Each row represents one thousand model runs with the shown factor set points, and the resulting averaged response.

b. Advanced Model Data

Each of the advanced scenario datasets consists of 200 design points, with every point run 50 times with prescribed values for each factor, resulting in 10,000 simulation runs. Since there are six advanced model scenarios being evaluated, the end product for the advanced data is 60,000 rows. Fortunately, given the available computational power present in the SEED Center at NPS, the generation of the data took an acceptable amount time.

As stated previously, the advanced scenarios are intended to help us understand and show the changes in factor importance when placed in differing environments. Keeping this in mind, the MOP of OPV systems is evaluated to a higher degree than the MOE of the baseline models. As an example, taking a look at OPV survival rates now becomes an important topic since it was impossible to lose an OPV during the baseline study. Additionally, given the changes to the OPV gun in the enhanced OPV scenarios, its MOP is expected to differ greatly from the baseline OPV scenarios.

2. Analysis Tool

a. JMP

Originally named John's Macintosh Project (JMP) prior to its release, JMP is a statistical analysis package that was developed for Macintosh machines in 1993 and later for Windows and Linux computers. Named after the developer, John Stall, JMP allows for extensive statistical analysis with graphical display and interactivity. With its ease of use and compatibility with a variety of data formats, JMP is a widely used tool for conducting simple and advanced data analysis. The edition utilized in this study is JMP 9 Pro (SAS Institute Inc., 2012).

3. Statistical vs. Practical Significance

During the course of the analysis, it is important to remember the difference between statistical and practical significance. Statistical significance is a function of the sample size, and indicates that the differences in the mean are not a result of chance and rejection of the null hypothesis is true. However, it does not indicate importance or the severity of these differences. This is shown by practical significance, which identifies if a difference in the response has real-world implications. An example being that a difference in mast height by 1 inch on an OPV may be statistically significant for SFAC detection purposes, but is the cost associated with designing and raising that mast practical.

C. INTERCHANGEABILITY

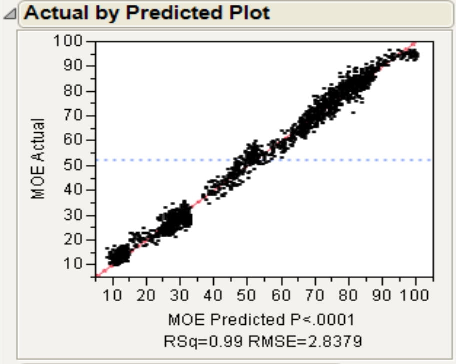
Prior to the implementation of the advanced modeling effort, the comparison of the baseline models needs to be conducted. The reason behind this is before advanced features available in MANA can be utilized, it has to be shown that both the OSN and baseline MANA models behave in very similar manners. This similarity in behaviors needs to be to such a level that they could be used interchangeably. The establishment of interchangeability would allow us to state that if the OSN model had all the capabilities utilized in the advanced MANA scenarios, that it should produce similar results.

Regression analysis and other techniques are utilized to establish interchangeability, and the analysis is shown below.

1. OSN Baseline Model Analysis

The first step down the road to interchangeability is the establishment of an objective to work towards, and for this research effort, it was the replication of the work performed by the OSN staff. Data produced from their efforts was made available to the OR students participating in the ASNET/PRONT NICOP Project. The focus of the effort was not to establish validation, but verification. This approach helps to confirm that the previous study was not influenced by unidentified factors or errors which may have impacted the outcome. To verify the OSN model, its output had to be presented, with its MOE and MOP of involved factors.

Actual by Predicted Plot



Summary of Fit

RSquare	0.988605
RSquare Adj	0.988485
Root Mean Square Error	2.837918
Mean of Response	52.30708
Observations (or Sum Wgts)	1920

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	20	1326859.3	66343.0	8237.495
Error	1899	15294.1	8.1	Prob > F
C. Total	1919	1342153.4		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	619	10670.127	17.2377	4.7717
Pure Error	1280	4624.000	3.6125	Prob > F
				<.0001*
Total Error	1899	15294.127		Max RSq
				0.9966

Figure 13. OSN Model Regression

The regression plot and statistical output in Figure 15 lays the initial baseline for the following NPS effort in regards to the ASUW scenario. The very high R-squared states that most of the variance in the data is accounted for by the model. Looking at the statistical output gives credence to the assumption that this model is a very good reflection of the real data, but a qualitative approach to looking at the Actual vs. Predicted Plot begins to generate questions.

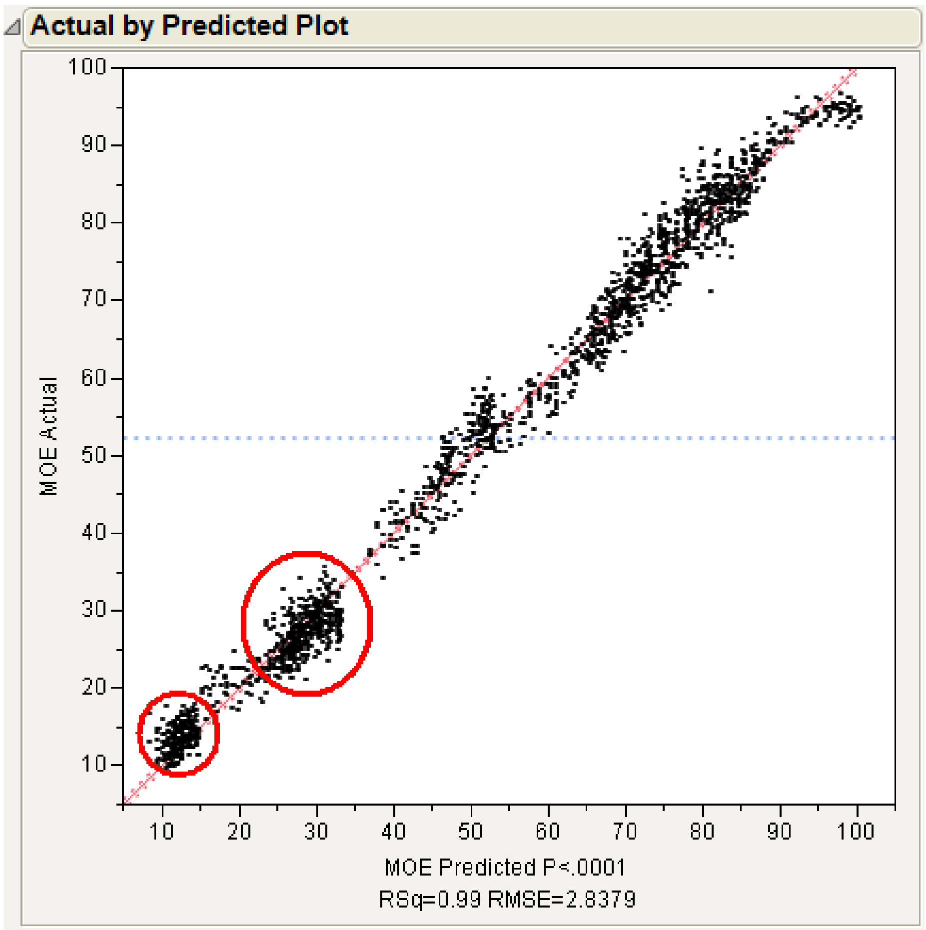


Figure 14. OSN Model Actual by Predicted Plot

The distinct groupings present in the plot infer that there may be particular factors which drastically influence the response. To try and identify these relationships, partition trees, sorted parameter estimates, or factor prediction profilers are a few of the tools available in JMP.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
GUN[0]	-23.58688	0.064766	-364.2	<.0001*
SSM[1]	-7.694375	0.064766	-118.8	<.0001*
HELO[0]	-5.307917	0.064766	-81.95	<.0001*
SFAC[1]	3.3035417	0.064766	51.01	<.0001*
Max Speed	0.5452525	0.011274	48.36	<.0001*
GUN[0]*HELO[0]	-2.922708	0.064766	-45.13	<.0001*
HELO[0]*SFAC[1]	-2.045208	0.064766	-31.58	<.0001*
GUN[0]*(Max Speed-31)	-0.344855	0.011274	-30.59	<.0001*
GUN[0]*SSM[1]	-1.551667	0.064766	-23.96	<.0001*
GUN[0]*SFAC[1]	-1.516667	0.064766	-23.42	<.0001*
HELO[0]*(Max Speed-31)	-0.244495	0.011274	-21.69	<.0001*
HELO[0]*SSM[1]	1.1352083	0.064766	17.53	<.0001*
MastH	0.2646389	0.01931	13.71	<.0001*
(Max Speed-31)*(Max Speed-31)	-0.022029	0.002228	-9.89	<.0001*
(Max Speed-31)*SFAC[1]	-0.107557	0.011274	-9.54	<.0001*
HELO[0]*(MastH-17.5)	0.1211944	0.01931	6.28	<.0001*
(Max Speed-31)*SSM[1]	0.0609533	0.011274	5.41	<.0001*
SFAC[1]*SSM[1]	0.2441667	0.064766	3.77	0.0002*
(MastH-17.5)*SSM[1]	-0.0675	0.01931	-3.50	0.0005*
(Max Speed-31)*(MastH-17.5)	-0.00942	0.003361	-2.80	0.0051*

Figure 15. OSN Model Sorted Parameter Estimates

Right off the bat, the naval gun factor stands out from the sorted parameter estimates plot of the OSN data, so the distinct groupings present in the regression plot may have some reliance on whether or not the gun is present in a simulation run.

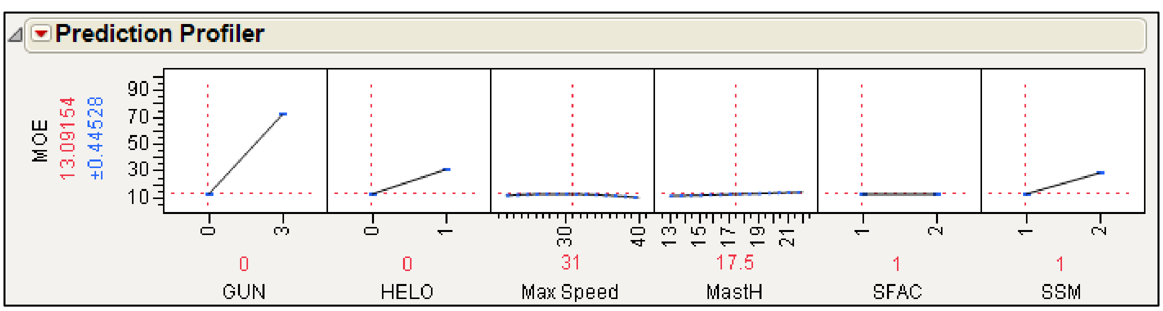


Figure 16. OSN Model Prediction Profiler Plot

Looking at the prediction profiler plot of the OSN data yields a similar conclusion; the gun factor has the largest impact on the response. As a reminder, the gun factor is binary: a value of 0 signifies the gun is absent from the OPV simulation, while a value of 3 represents the presence of the gun that has three shots available to prosecute the SFACs.

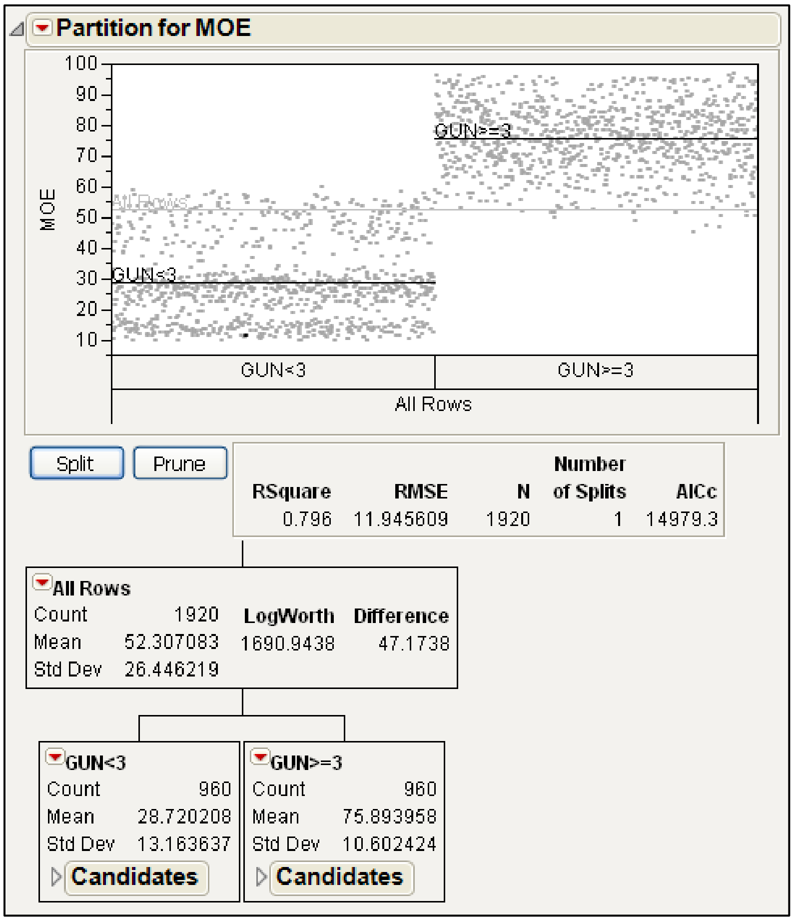


Figure 17. OSN Model Partition Tree Plot (1st Split)

From the partition tree projection of the OSN model data, with the very first split, the gun factor establishes itself as the key deciding factor in regards to the response. Additionally, with just one factor, 79.6% of all variation in the data is being accounted for according to the R-squared value in Figure 19.

With each of the three previous analysis tools pointing toward the naval gun factor as being the most significant, trying to understand how this factor is impacting the regression model in the creation of the distinct groupings is of importance. To do this, JMP's user interface (UI) can be employed to select all data points associated with the presence of the naval gun factor, or, its absence.

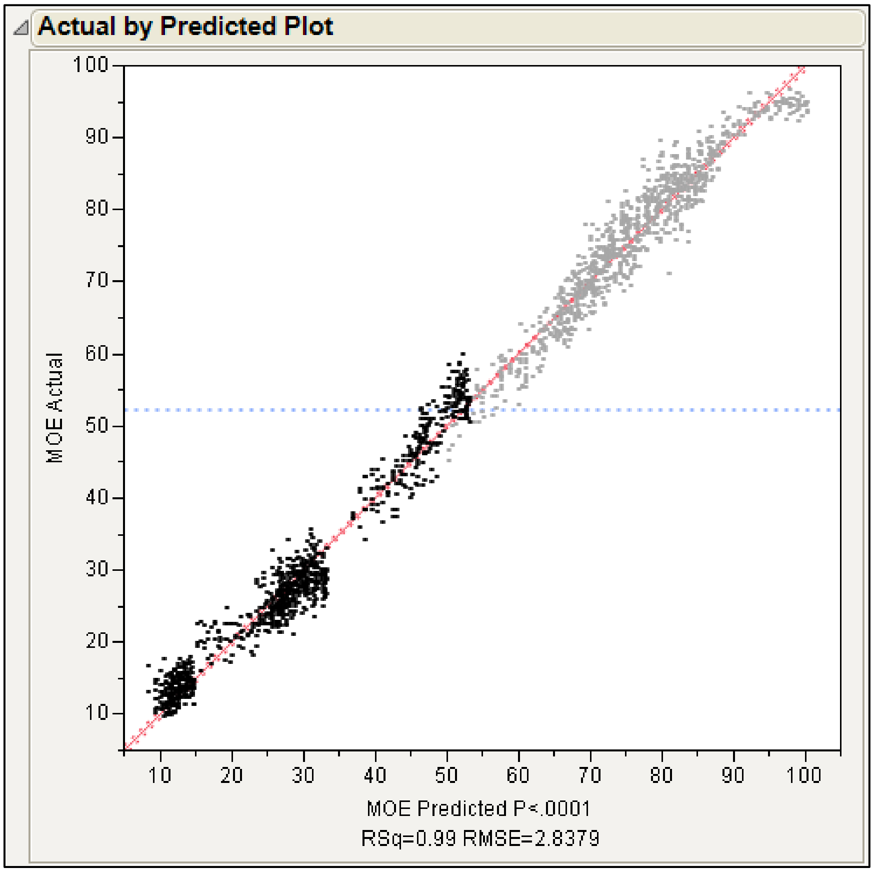


Figure 18. OSN Model Actual by Predicted Plot (Gun absent selection)

With the specific selection of all rows of data in the OSN model output without the presence of a naval gun, it can clearly be seen that both of the lower groupings and the later portion of the larger grouping are included. This implies, along with the previous analysis results, that the naval gun is the most significant factor impacting model response. Yet it does not explain the full picture in regards to the groupings since both of the smaller groups lie within the data set missing the gun factor, so additional factors may be impacting the creation of the lower performance groupings.

The other realized piece of information from Figure 20 is that regardless of the rest of the OPV armaments or performance capabilities, the inclusion of the naval gun produces results in the upper half of all model simulation runs. While some overlap between the gun being present and not being present exists, the vast majority of available data existing above the Mean Response of 52.3 involves the inclusion of the gun factor.

Referencing Figure 17 again, the Surface to Surface Missile (SSM) factor, or OPV Missile Type, is the next factor with the highest T-ratio, meaning that it is both statistically significant, and strongly defeats the null hypothesis. Checking the partition tree further shows its importance to the OSN modeling analysis.

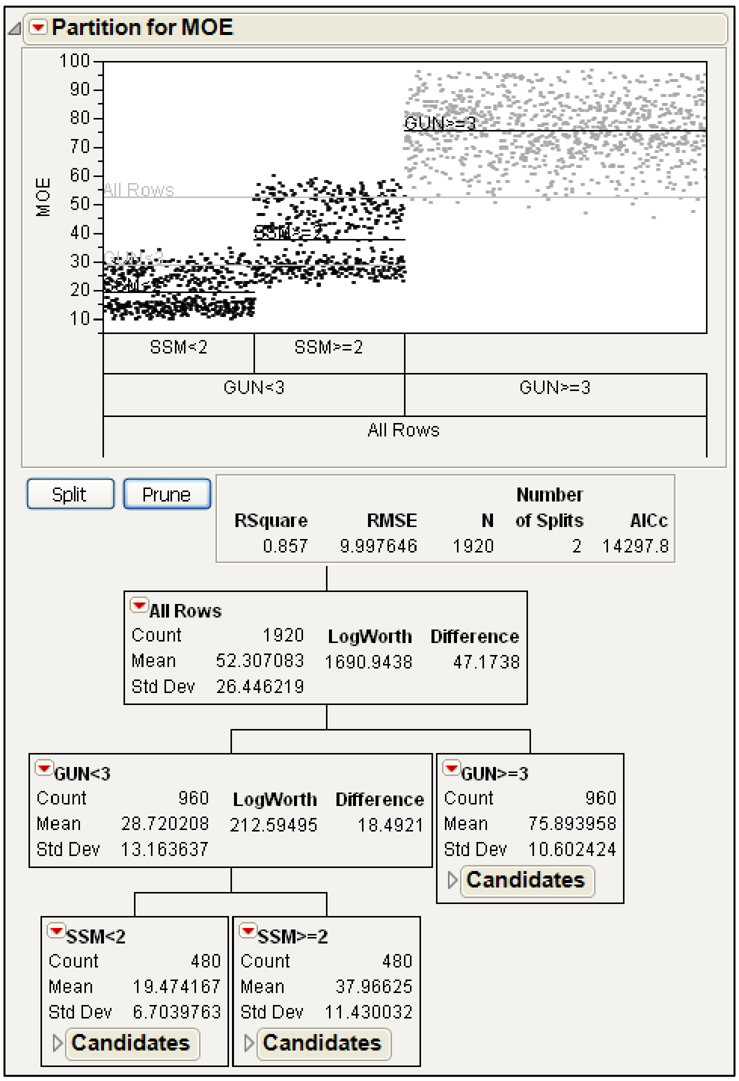


Figure 19. OSN Model Partition Tree Plot (2nd Split)

Confirming the result shown in Figure 17 in regards to SSM importance, Figure 21 shows that which OPV missile type is equipped has the second largest impact on the response following the naval gun. The increase in R-Squared also shows its importance given that the SSM factor raised R-Squared by almost 6% from the previous 79.6% established by the gun factor. With this result in mind, the picture concerning the regression plot groupings begins to clear, and a relation between the two factors may be the reason behind the groupings.

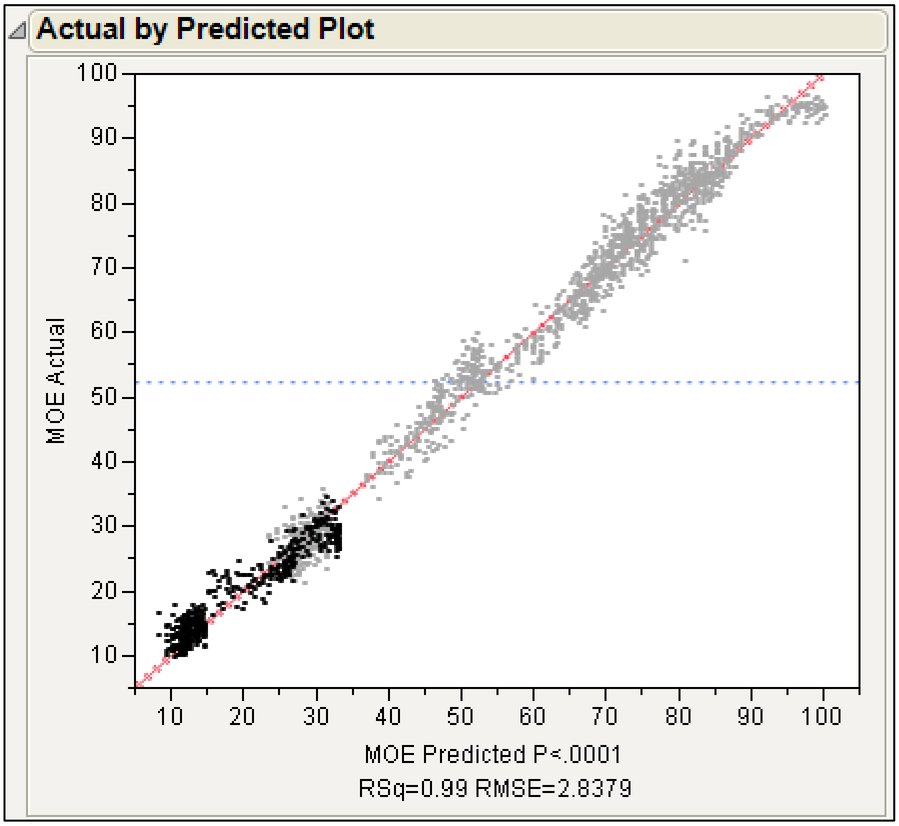


Figure 20. OSN Model Actual by Predicted Plot (Gun Absent & SSM 1 Equipped)

In Figure 20, the data highlighted identifies OPVs lacking a naval gun and having SSM 1 equipped. The highlighted data accounts for all data points located in the lowest grouping, as well as a portion of the next higher grouping. This result passes the common sense test since a warship equipped with the poorest weapon system, and lacking a gun to prosecute a threat would be expected to perform below par. For the other portion of data in the second grouping, looking at Figure 17 again shows that the presence of the helicopter is the next most important factor.

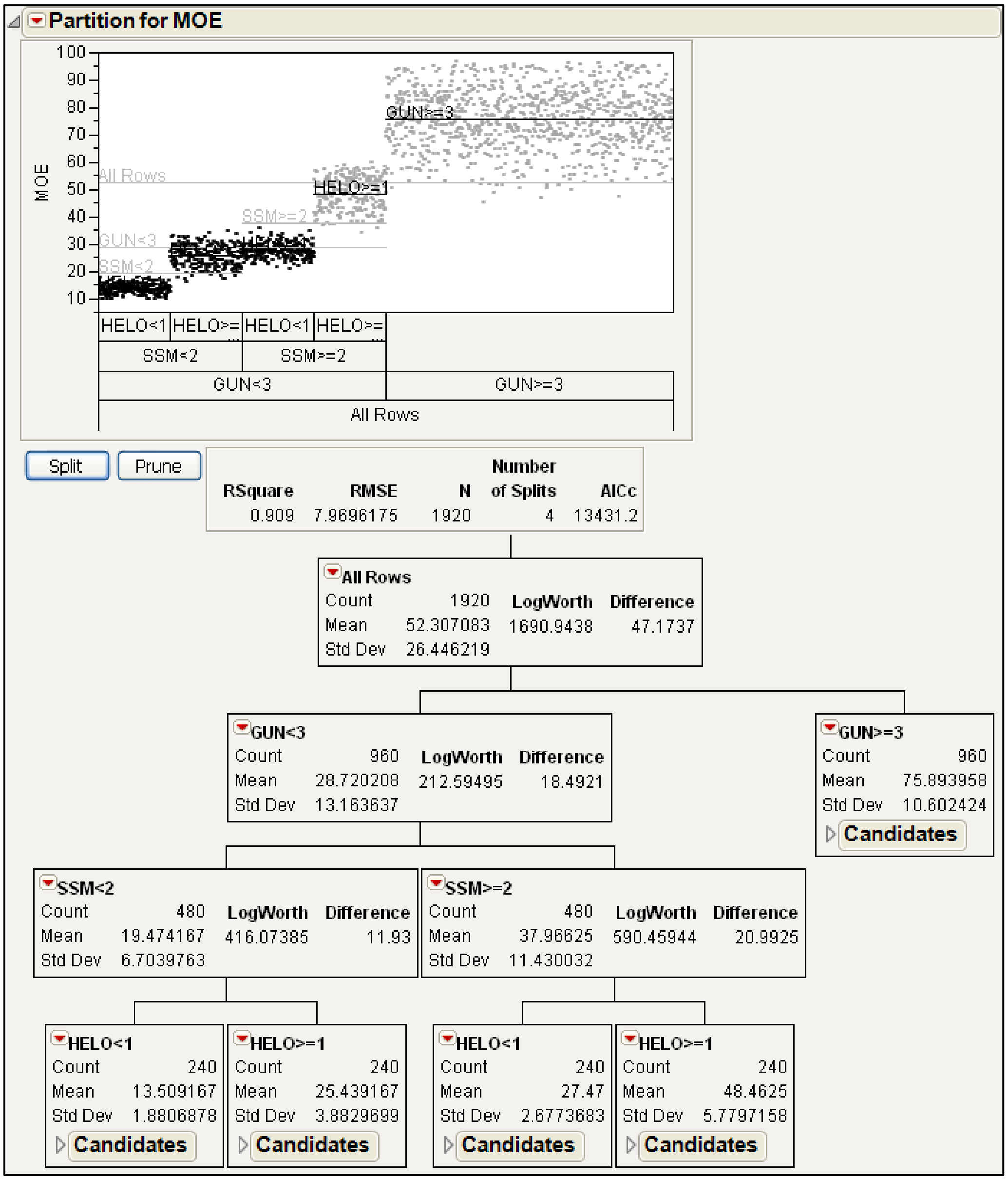


Figure 21. OSN Model Partition Tree Plot (Splits 1- 4)

Figure 23 reaffirms the previous statement that a helicopter feeding data to the patrolling OPVs is the next most significant factor. The information distribution capability provided by the helicopter in the simulations drastically increases the OPV detection effectiveness, and allows for missile engagements on the SFACs to be taken at significantly longer ranges.

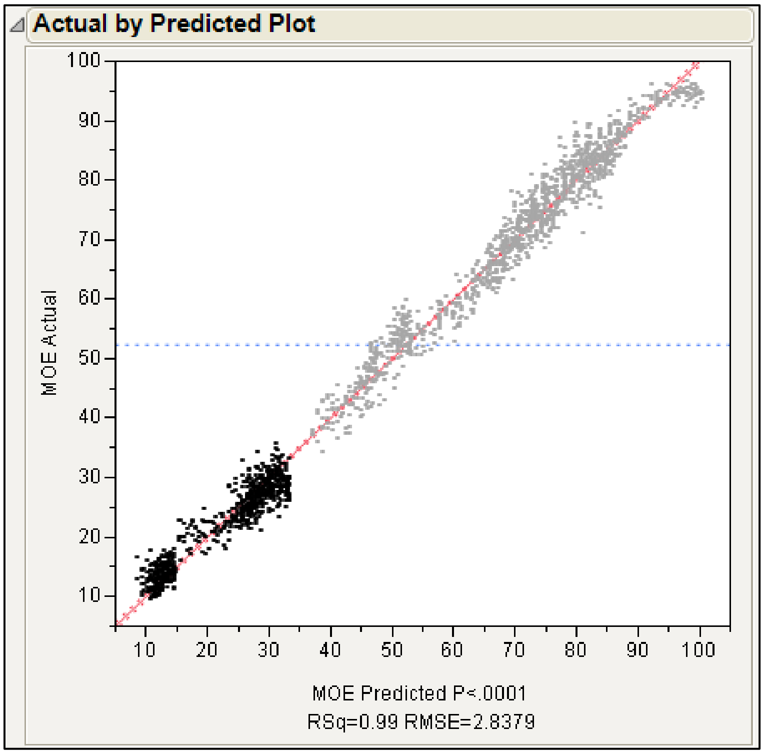


Figure 22. OSN Model Actual by Predicted Plot (Gun & Helicopter Absent, SSM 1)

To confirm the result from Figure 23, Figure 24 shows that exclusion of the naval gun and the helicopter providing tactical data creates a worst case situation for the OPVs with the SSM 1 missile system is equipped, regardless of speed of the OPV, LWL, or which type of threat they are facing.

a. Length at Waterline

As previously mentioned, the MANA baseline model was unable to account for OPV length at waterline, which was included in the OSN modeling effort.

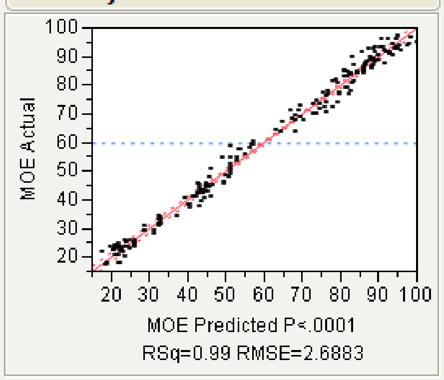
Referencing Figure 17 shows that neither the LWL factor, nor any interactions with this factor were deemed statistically significant to the OSN model regression. Ultimately this means that the LWL factor can be removed from consideration because it does not impact model performance. This does not however mean that LWL is not important for ship synthesis considerations, because the length of a naval vessel does indeed impact speed, maneuverability, weight, and equipment spacing considerations. Given the simplicity of the modeling effort at hand, ship synthesis considerations were not accounted for in the OSN model, since its primary focus was on agent behavior and factor significance.

2. MANA Baseline Model Analysis

Repeating a similar analysis process to the data generated by the MANA baseline model helps in establishing interchangeability. Just like in the OSN model analysis, determining overall model effectiveness is the initial focus.

Response MOE

Actual by Predicted Plot



Summary of Fit

RSquare	0.990288
RSquare Adj	0.989323
Root Mean Square Error	2.688327
Mean of Response	59.702
Observations (or Sum Wgts)	200

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	18	133386.63	7410.37	1025.359
Error	181	1308.10	7.23	Prob > F
C. Total	199	134694.74		<.0001*

Figure 23. MANA Baseline Model Regression

Since the data are averaged much in the same way as the OSN data, a very large portion of the variance in the data is accounted for by the regression model, as shown by the R-Squared of 99%. This results in the similar statement that the regression is a good predictor of model behavior in regards to averaged results. Looking at the Actual by Predicted Plot qualitatively begins to produce observations similar to the OSN data.

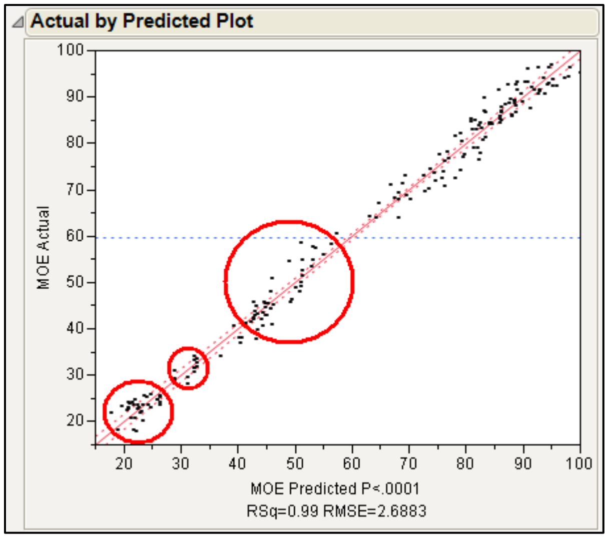


Figure 24. MANA Baseline Model Actual by Predicted Plot

Formation of groupings become apparent, just as in the OSN data, so again this points to key factors that have significant impacts on simulation performance.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
GUN[0]	-23.82966	0.193253	-123.3	<.0001*
SSM[1]	-7.879604	0.191331	-41.18	<.0001*
GUN[0]*SSM[1]	-3.111291	0.192275	-16.18	<.0001*
SFAC[1]	3.1092659	0.193651	16.06	<.0001*
GUN[0]*HELO[0]	-2.185405	0.19593	-11.15	<.0001*
GUN[0]*SFAC[1]	-2.021213	0.192331	-10.51	<.0001*
Max Speed	0.3752795	0.037235	10.08	<.0001*
GUN[0]*(Max Speed-31)	-0.339607	0.036991	-9.18	<.0001*
HELO[0]*SFAC[1]	-1.660048	0.193022	-8.60	<.0001*
HELO[0]	-1.595087	0.192833	-8.27	<.0001*
MastH	0.4607811	0.057739	7.98	<.0001*
HELO[0]*(Max Speed-31)	0.1473936	0.037513	3.93	0.0001*
HELO[0]*SSM[1]	0.6670687	0.19694	3.39	0.0009*
(Max Speed-31)*SSM[1]	0.1109279	0.037152	2.99	0.0032*
(MastH-17.5)*SSM[1]	-0.157897	0.059798	-2.64	0.0090*
(MastH-17.5)*(MastH-17.5)	-0.055664	0.021861	-2.55	0.0117*
SFAC[1]*SSM[1]	0.490686	0.193845	2.53	0.0122*
GUN[0]*(MastH-17.5)	0.1330198	0.059346	2.24	0.0262*

Figure 25. MANA Baseline Model Sorted Parameter Estimates

The naval gun again, appears to be the major contributing factor in regards to the response, followed by the SSM factor. However, initial observations indicate that the helicopter factor, while still significant, no longer carries as much importance individually, but relies more so on its interaction with other factors. This maybe the result of difference in computation calculations inherent to MANA or the OSN C++ coding, or modeling differences, but its impact is addressed later.

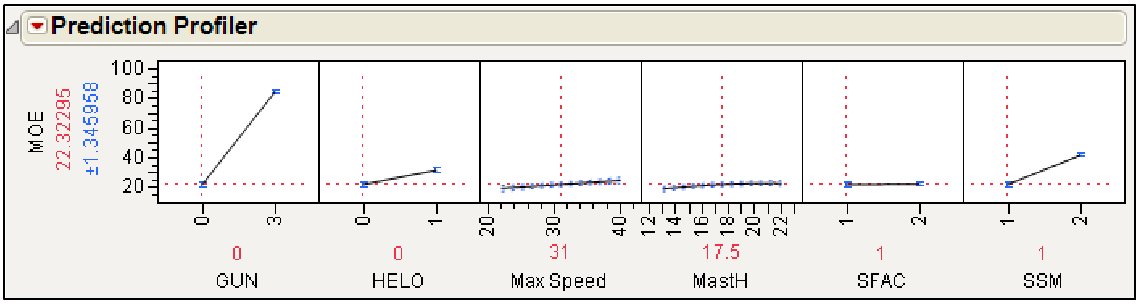


Figure 26. MANA Baseline Model Prediction Profiler Plot

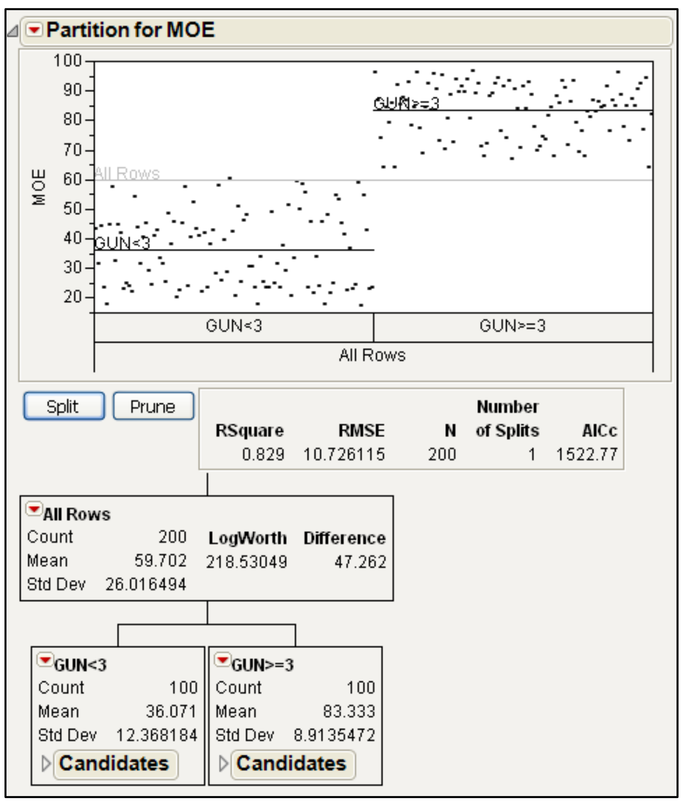


Figure 27. MANA Baseline Model Partition Tree Plot (1st Split)

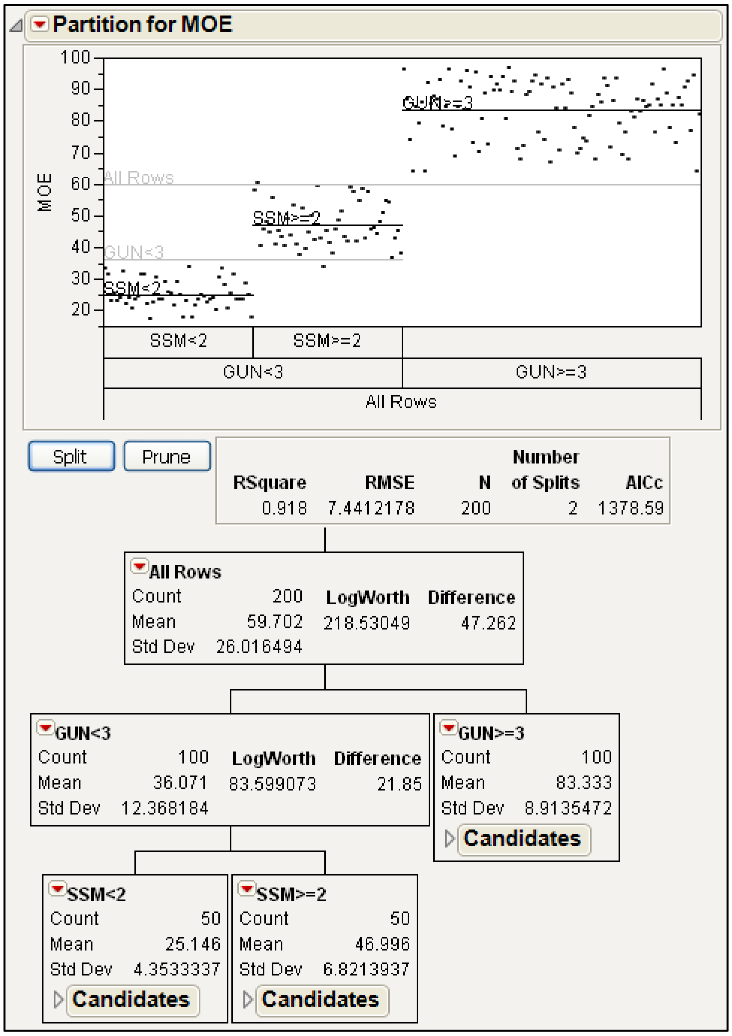


Figure 28. MANA Baseline Model Partition Tree Plot (2nd Split)

To help affirm the significance of the naval gun and SSM factors, like in the OSN model, prediction profiler and partition tree plots have been generated. As shown in Figure 29, the naval gun factor accounts for 82.9% of all variation in the model, slightly more, but similar to the naval gun in the OSN model. The SSM factor also contributes to a fair portion of the variation with an 8.28% increase in R-Squared, similar, but again slightly more than the OSN model.

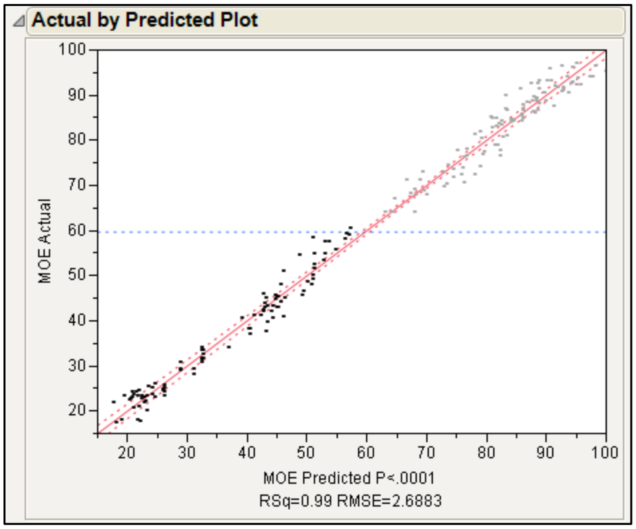


Figure 29. MANA Baseline Model Actual by Predicted Plot (Gun Absent Selection)

Addressing the groups highlighted in Figure 26, specific selection of the rows of data where the naval gun was missing from the simulation generates a plot similar to Figure 20, as shown by Figure 31. This behavior reflects the OSN model, and the same statement can be made that regardless of the other factors, exclusion of the naval gun from the simulation model results with an MOE in the lower half of the spectrum.

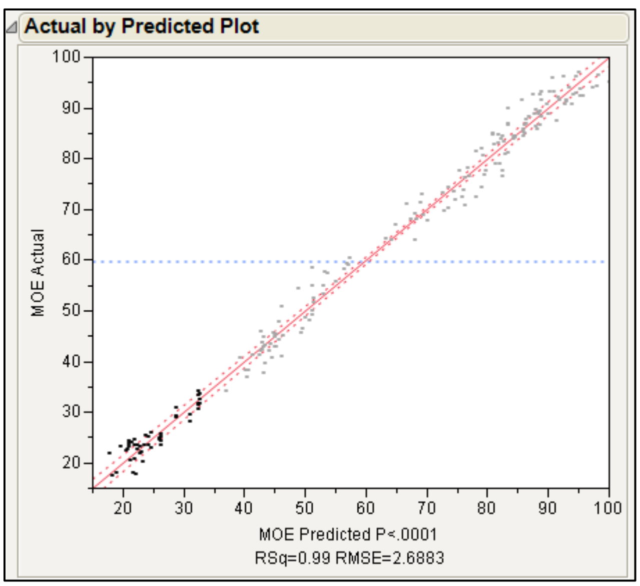


Figure 30. MANA Baseline Model Actual by Predicted Plot (Gun Absent & SSM 1 Equipped)

Reflecting similar outcomes to the OSN model in Figure 22, Figure 32 shows that OPVs not equipped with a naval gun and employing the less capable missile system performs poorly in regards to the ASUW scenario presented. This and the previous demonstrations of similarity between the models is a good indication that interchangeability may in fact be possible, but there are differences present, as shown by additional splits of the partition tree for the MANA baseline data.

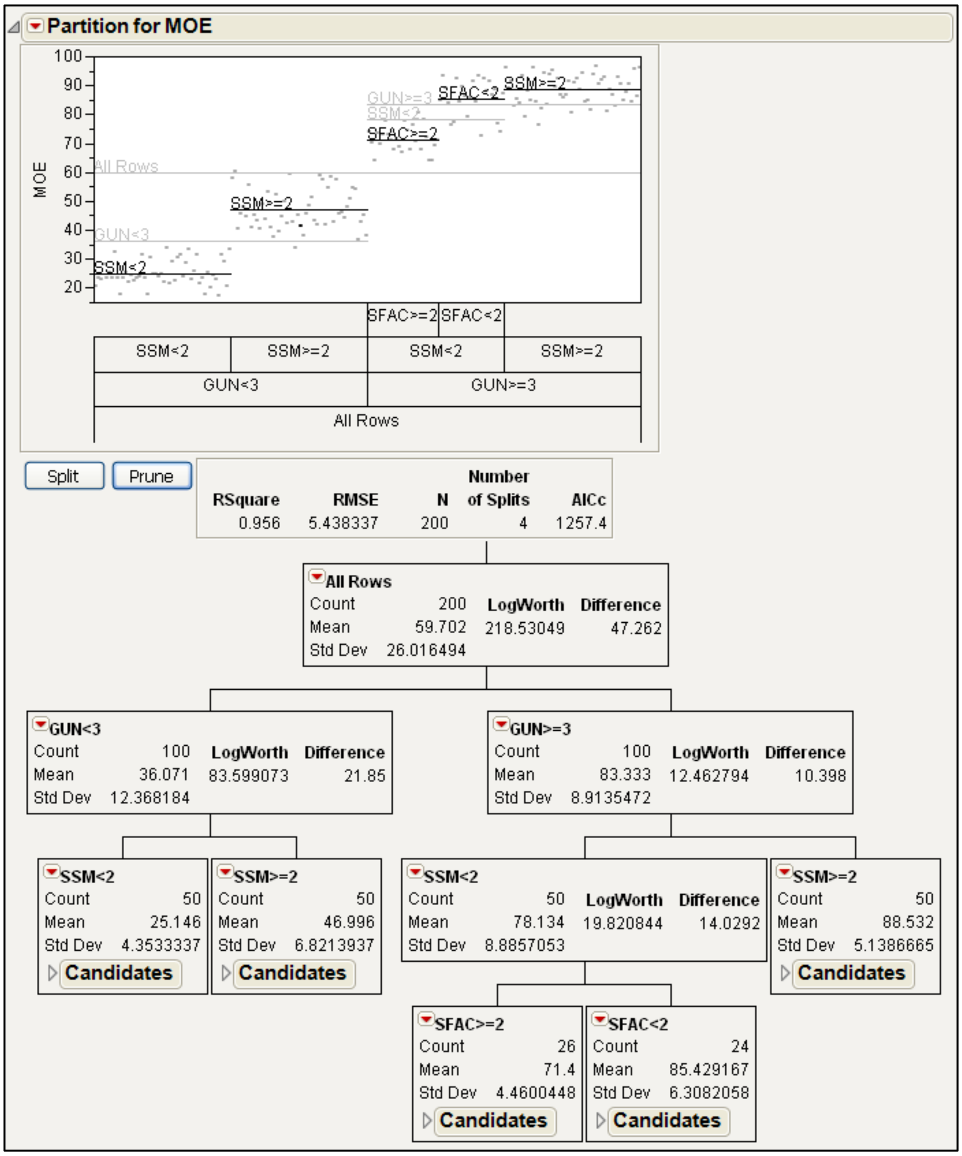


Figure 31. MANA Baseline Model Partition Tree (Splits 1 - 4)

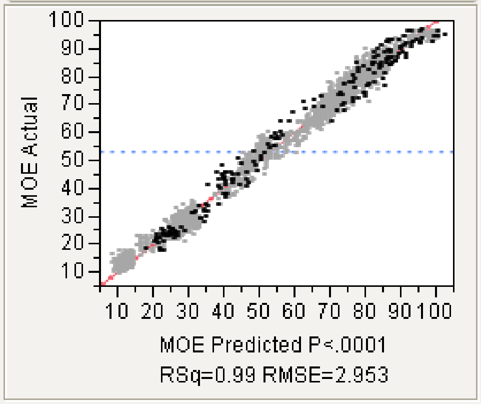
Unlike Figure 23, which focused on the portion of data missing the naval gun factor, the MANA baseline model partition tree begins to address branches for both factor levels. When the naval gun is absent or present, the missile system on the OPV is the next most important factor, but following this, what type of enemy, either SFAC type one or type two is more important. This diverges from the helicopter factor in the OSN model, yet comparing the factor importance between Figure 17 and Figure 27, there is still a close similarity between the two models. However, this comparison is insufficient to ascertain interchangeability. To accomplish this goal, a combination of both data sets is required, as well as supplying an additional factor identifying what rows of data originate from which sets of data. This factor is nothing more than an indicator variable, but it holds the key in establishing interchangeability.

3. Combined Model Data Analysis

Just as for the OSN and MANA baseline models, the combined data of the two is be used to generate a regression model, with sorted parameter estimates, partition trees, and prediction profiles to help identify factor significance.

Response MOE

Actual by Predicted Plot



Summary of Fit

RSquare	0.987712
RSquare Adj	0.987572
Root Mean Square Error	2.95299
Mean of Response	53.00472
Observations (or Sum Wgts)	2120

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	24	1468484.6	61186.9	7016.721
Error	2095	18268.7	8.7	**Prob > F**
C. Total	2119	1486753.3		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
				4.6345
Lack Of Fit	815	13644.714	16.7420	**Prob > F**
Pure Error	1280	4624.000	3.6125	<.0001*
Total Error	2095	18268.714		**Max RSq**
				0.9969

Figure 32. Combined Data Regression (MANA Data Selected)

For ease of identification, the data produced by the MANA baseline model have been selected in Figure 34 and Figure 35, and from the statistical output it seems that the regression model is accounting for a very large portion of the variance based upon the high R-squared value. This behavior is present in both regressions of the individual data sets, and since both sets of data feed responses that are averaged, it is reasonable to assume that the resulting combination of the data would produce a regression model accounting for most of the variation as well.

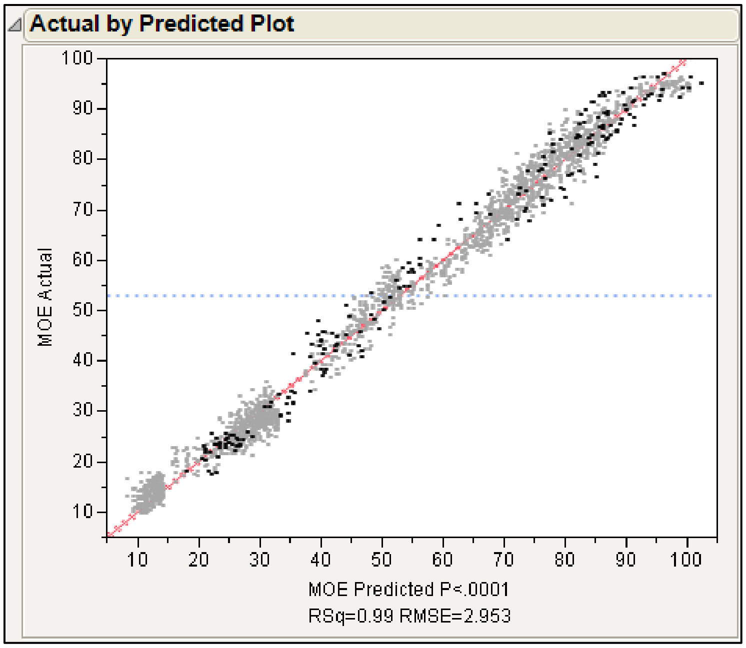
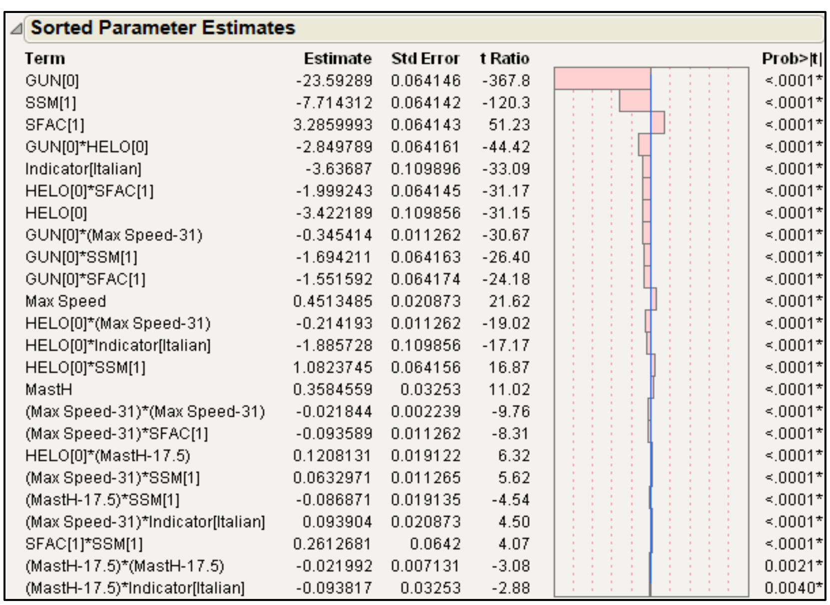


Figure 33. Combined Data Actual by Predicted Plot

A qualitative look at the actual by predicted plot in Figure 35 seems to indicate a shift of the MANA baseline data toward better results that the OSN data. To investigate this occurrence, identifying the impact of the indicator variable previously mentioned needs to take place.

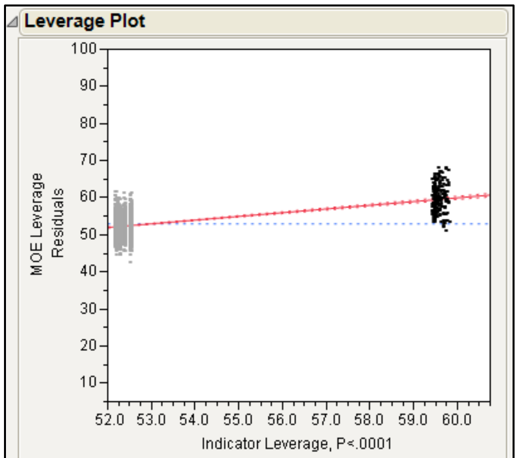


Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
GUN[0]	-23.59289	0.064146	-367.8	<.0001*
SSM[1]	-7.714312	0.064142	-120.3	<.0001*
SFAC[1]	3.2859993	0.064143	51.23	<.0001*
GUN[0]*HELO[0]	-2.849789	0.064161	-44.42	<.0001*
Indicator[Italian]	-3.63687	0.109896	-33.09	<.0001*
HELO[0]*SFAC[1]	-1.999243	0.064145	-31.17	<.0001*
HELO[0]	-3.422189	0.109856	-31.15	<.0001*
GUN[0]*(Max Speed-31)	-0.345414	0.011262	-30.67	<.0001*
GUN[0]*SSM[1]	-1.694211	0.064163	-26.40	<.0001*
GUN[0]*SFAC[1]	-1.551592	0.064174	-24.18	<.0001*
Max Speed	0.4513485	0.020873	21.62	<.0001*
HELO[0]*(Max Speed-31)	-0.214193	0.011262	-19.02	<.0001*
HELO[0]*Indicator[Italian]	-1.885728	0.109856	-17.17	<.0001*
HELO[0]*SSM[1]	1.0823745	0.064156	16.87	<.0001*
MastH	0.3584559	0.03253	11.02	<.0001*
(Max Speed-31)*(Max Speed-31)	-0.021844	0.002239	-9.76	<.0001*
(Max Speed-31)*SFAC[1]	-0.093589	0.011262	-8.31	<.0001*
HELO[0]*(MastH-17.5)	0.1208131	0.019122	6.32	<.0001*
(Max Speed-31)*SSM[1]	0.0632971	0.011265	5.62	<.0001*
(MastH-17.5)*SSM[1]	-0.086871	0.019135	-4.54	<.0001*
(Max Speed-31)*Indicator[Italian]	0.093904	0.020873	4.50	<.0001*
SFAC[1]*SSM[1]	0.2612681	0.0642	4.07	<.0001*
(MastH-17.5)*(MastH-17.5)	-0.021992	0.007131	-3.08	0.0021*
(MastH-17.5)*Indicator[Italian]	-0.093817	0.03253	-2.88	0.0040*

Figure 34. Combined Data Sorted Parameter Estimates

Just like with the individual analysis of the baseline datasets, the sorted parameter estimates shown in Figure 36 indicate that again the naval gun and SSM factors play as the most significant factors in the combined model. However, the indicator variable, annotated Indicator[Italian] places fifth in importance to other factors, which means any difference between the models is dominated by four factor effects, including the helicopter due to its interactions.

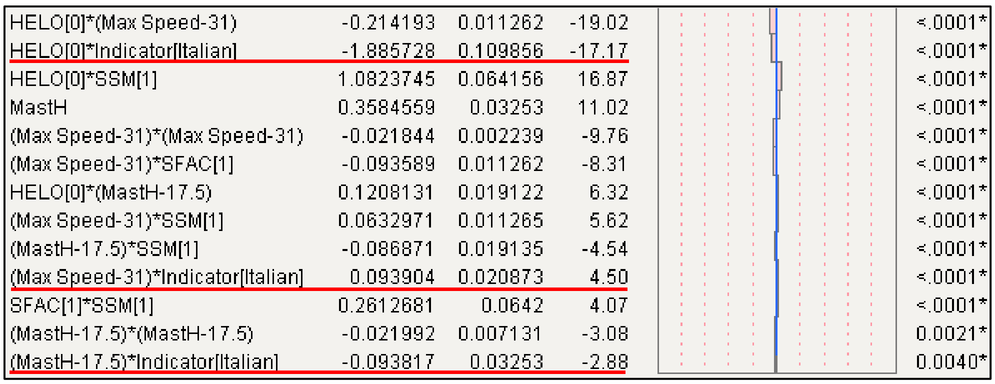


Least Squares Means Table

Level	Least Sq Mean	Std Error	Mean
Italian	53.275344	0.12824197	52.3071
NPS	60.549083	0.23233679	59.7020

Figure 35. Leverage Plot for Indicator Variable

Figure 37 shows there exists a statistically significant difference between both sets of data, both qualitatively and quantitatively since the least square means of both data sets differs by 7.27. This improved performance by the MANA baseline model can be the result of a whole host of different factors, be they programming differences, behaviors in hit probability calculations, or agent targeting criteria inherent to MANA or the C++ code. Whatever the reason behind the difference in mean responses between the two data sets is actually irrelevant. What is important is model behavior. As previously shown, both models behave very closely in regards to key factor importance, but the true test in determining if the models are behaving similarly is by analyzing the interactions of factors with the indicator variable. If no interactions exist, then the difference between the two models can easily be removed by the inclusion of a correction factor to help shift one regression onto the other, ie; the indicator variable. If interactions with the indicator variable do exist however, then the problem becomes more complicated since the slopes of the regression lines are different, and it is possible to state that the change in model response is a function of which data set being viewed. This outcome is undesirable, so scrutinizing the sorted parameter estimates for indicator interactions is necessary.



HELO[0]*(Max Speed-31)	-0.214193	0.011262	-19.02	<.0001*
HELO[0]*Indicator[Italian]	-1.885728	0.109856	-17.17	<.0001*
HELO[0]*SSM[1]	1.0823745	0.064156	16.87	<.0001*
MastH	0.3584559	0.03253	11.02	<.0001*
(Max Speed-31)*(Max Speed-31)	-0.021844	0.002239	-9.76	<.0001*
(Max Speed-31)*SFAC[1]	-0.093589	0.011262	-8.31	<.0001*
HELO[0]*(MastH-17.5)	0.1208131	0.019122	6.32	<.0001*
(Max Speed-31)*SSM[1]	0.0632971	0.011265	5.62	<.0001*
(MastH-17.5)*SSM[1]	-0.086871	0.019135	-4.54	<.0001*
(Max Speed-31)*Indicator[Italian]	0.093904	0.020873	4.50	<.0001*
SFAC[1]*SSM[1]	0.2612681	0.0642	4.07	<.0001*
(MastH-17.5)*(MastH-17.5)	-0.021992	0.007131	-3.08	0.0021*
(MastH-17.5)*Indicator[Italian]	-0.093817	0.03253	-2.88	0.0040*

Figure 36. Excerpt From Sorted Parameter Estimates of Combined Data

As shown in Figure 38, there exist three statistically significant interaction terms with the indicator variable. With this in mind, analysis of their impact on the combined model can be performed to better understand their influence on model behavior.

		R-Squard	Delta
	Full Model	0.987712	
Indicator Interaction Factors Removed			
	Helicopter & Indicator	0.985984	0.001728
	Mast Height & Indicator	0.987664	4.8E-05
	Speed & Indicator	0.987594	0.000118
	Helicopter & Indicator, Mast Height & Indicator	0.985935	0.001777
	Helicopter & Indicator, Speed & Indicator	0.985866	0.001846
	Mast Height & Indicator, Speed & Indicator	0.987545	0.000167
	ALL Indicator Interactions	**0.985847**	**0.001865**

Table 4. Impact on R-Squared With Indicator Interactions Removal

Since Figure 38 shows that there are statistically significant interactions terms with the indicator variable, systematically removing these interactions from the combined dataset model can be carried out to understand their impact on accounting for model variation. Table 4 shows the indicator interaction removal process, from each individual interaction removed to all three interactions, and every combination in between. The Delta column represents the difference in R-Squared from the full model, to a model with the removed interaction terms prescribed. The end result from analyzing Table 4 is that even if all indicator interaction terms are removed from the combined model, they account for less than 0.2% of all variation explained by the regression. This ultimately means that while statistically significant, the indicator interaction terms are negligible in relation to model behavior and performance, and with the inclusion of the indicator variable for correction purposes, the two baseline models can be deemed as interchangeable. With this condition established, factor and interaction significance can be determined to establish the basis for the advanced model comparisons.

4. Baseline Factor Significance

With the establishment that both the MANA and OSN baseline models can be used interchangeably, the next focus of the analysis is the breakdown of factor significance on prosecuting SFAC agents. This means a shift from the MOE of successful goal line defense, to the MOP of OPV factors that impact SFAC termination. Unfortunately, the OSN data does not include the number of SFACs terminated for a single simulation run; however, the MANA baseline data does, and the average number of SFAC killed becomes the new measure of performance for the simulated OPVs. The analysis focuses on each of the specific factors utilized in the model and any particular interactions that significantly account for variation in the model.

a. Naval Gun

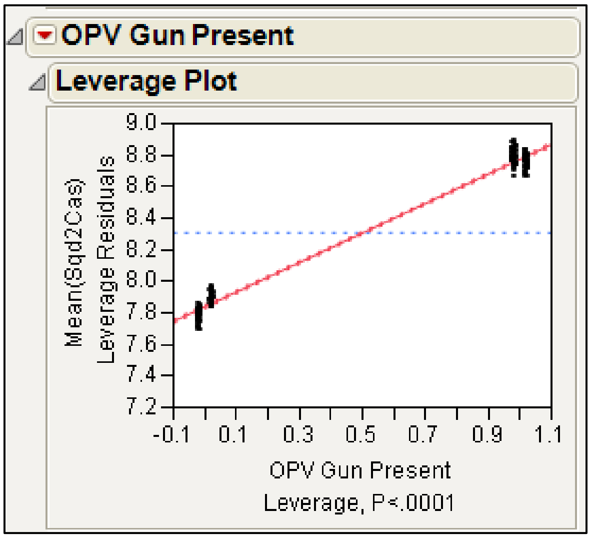


Figure 37. Baseline Naval Gun Leverage Plot

From Figure 39, the naval gun is shown to still be the most significant factor in determining OPV performance in regards to SFAC kills. The tight grouping to the left represents OPV performance the naval gun's absence, while the right grouping represents its availability.

b. Surface to Surface Missile Type

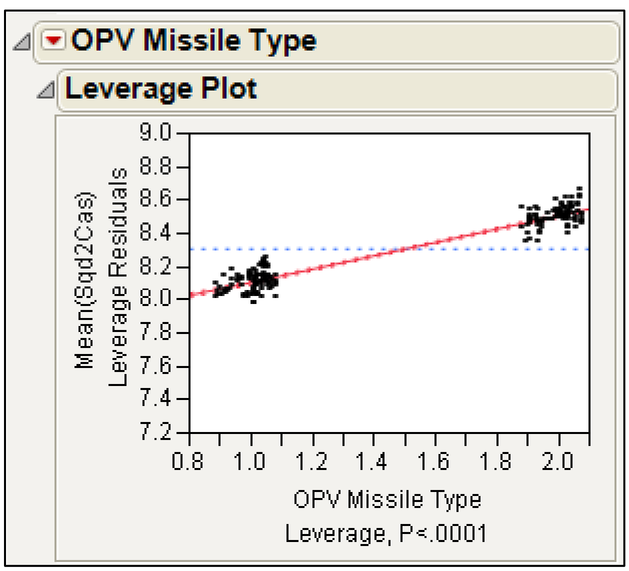


Figure 38. Baseline SSM Leverage Plot

Like the naval gun, SSM configuration on the OPV plays a huge part on performance in the ASUW scenario. This impact is largely due to the higher hit accuracy of the missile systems relative to the naval gun. Unfortunately SSM performance can be limited by the exclusion of the helicopter from a simulation run, unlike the naval gun. Additionally, after the expenditure of all missiles available on the OPVs have taken place, if SFACs still remain on the battlefield then the naval gun is the only possible alternative to achieve mission success. This is why the gun is plays a larger role than the missile system, even though the majority of SFAC kills have occurred due to missile strikes.

c. SFAC Type

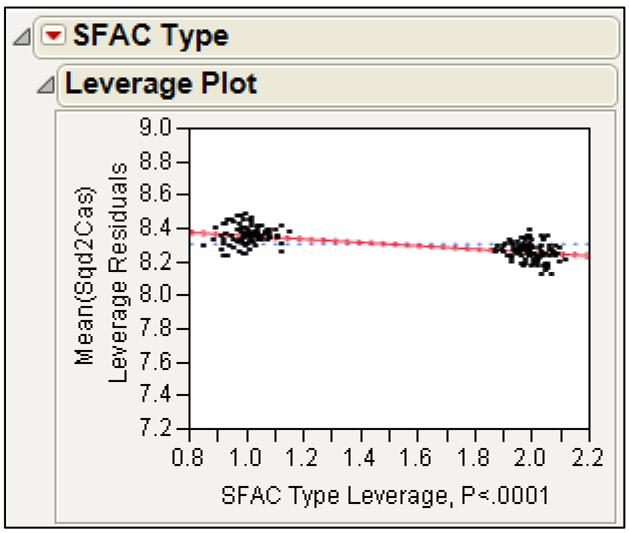


Figure 39. SFAC Type Leverage Plot

While providing not as quite a drastic impact on the MOP of number of SFAC kills, the SFAC type factor does play a big part in simulation results. The type of SFAC the OPVs are dealing with greatly increases or decreases the radar performance since it is inherently harder to detect smaller objects at sea. Additionally, larger SFACs are capable of mounting more powerful engines, and can potentially outrun defending OPVs. The end result is a decrease in mean response of 6.57. This passes the common sense test that OPV effectiveness should degrade when combating a swifter foe.

d. *OPV Radar Height*

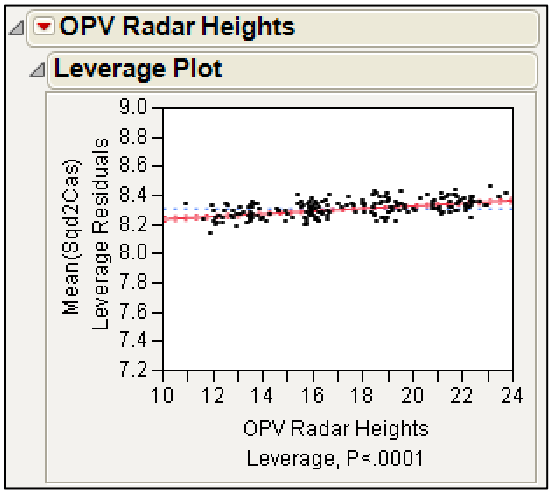


Figure 40. OPV Radar Height Leverage Plot

As shown by Figure 42, the leverage of OPV radar height is low relative to the gun or type of SSM. While having an effective surface search radar is important to detect the small boat threat, for this particular simulation, effects such as poor sea-state or curvature of the earth were not modeled, so radar height relatively important. This may not be the case in a simulation that accounts for such noise variables.

e. *Helicopter Presence*

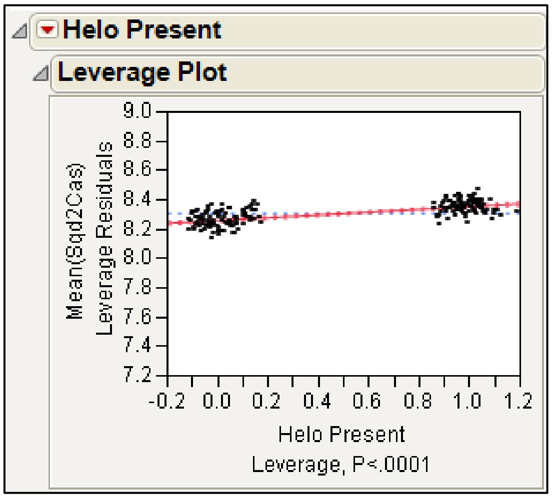


Figure 41. Helicopter Presence Leverage Plot

Similar in behavior to the OPV radar height factor, the helicopter provided additional tactical range to the OPVs in their detection and prosecution of approaching SFACs. Since issues such as weather or line of sight issues were not considered, the importance of the helicopter may be being undermined. However, the helicopter did increase OPV performance in killing SFACs, which was expected.

f. OPV Max Speed

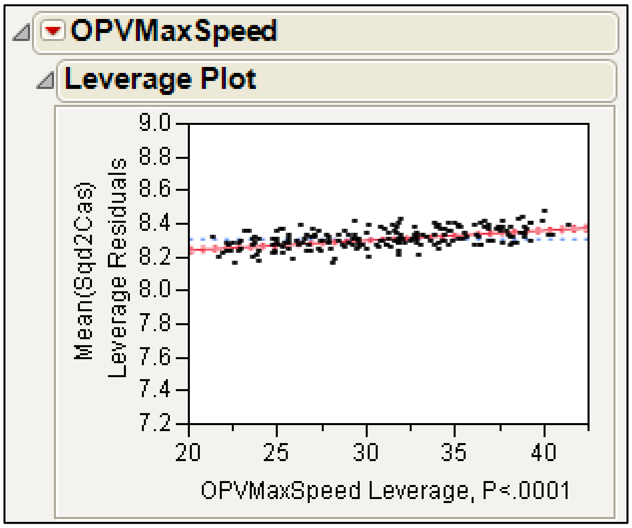


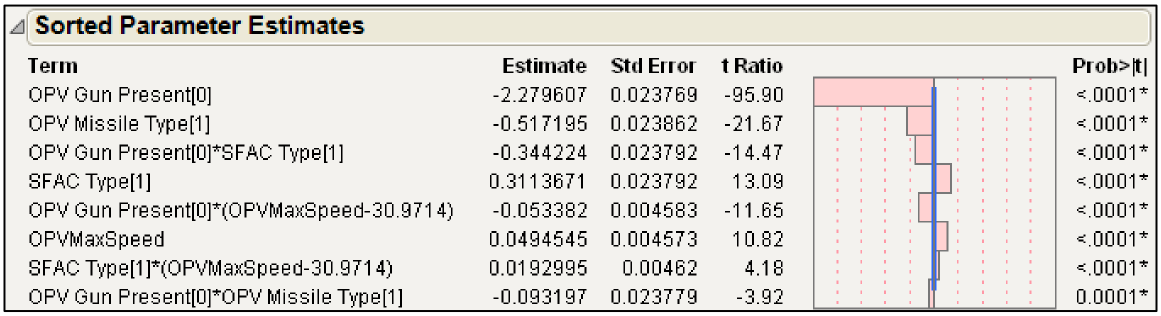
Figure 42. OPV Max Speed Leverage Plot

Once SFACs are detected, the maximum speed of OPVs has some, but not a lot, of impact on SFAC kills, as shown in Figure 44. This outcome has more to do with the capabilities of the equipped missile systems, detection ranges, and behaviors of the OPV agents in the simulation. The reason is that in many situations, a slower but better equipped OPV may be at least as effective as a faster, but less equipped one. In general, a faster OPV means that it can get in range quicker to kill approaching SFACs, but it first has to detect them. It then may have weapons capable of striking targets immediately, regardless of maximum speed.

D. ADVANCED MODEL ANALYSIS

1. Avoidance SFACs vs. Baseline OPVs

As stated in the methodology section, in the avoidance situation the SFACs are attempting to circumvent their OPV opponents. Since the number of SFACs involved has been doubled, the MOE of goal line defense has been removed, while focusing on OPV MOPs has become more important.


Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
OPV Gun Present[0]	-2.279607	0.023769	-95.90	<.0001*
OPV Missile Type[1]	-0.517195	0.023862	-21.67	<.0001*
OPV Gun Present[0]*SFAC Type[1]	-0.344224	0.023792	-14.47	<.0001*
SFAC Type[1]	0.3113671	0.023792	13.09	<.0001*
OPV Gun Present[0]*(OPVMaxSpeed-30.9714)	-0.053382	0.004583	-11.65	<.0001*
OPVMaxSpeed	0.0494545	0.004573	10.82	<.0001*
SFAC Type[1]*(OPVMaxSpeed-30.9714)	0.0192995	0.00462	4.18	<.0001*
OPV Gun Present[0]*OPV Missile Type[1]	-0.093197	0.023779	-3.92	0.0001*

Figure 43. Avoidance vs. Baseline OPV Sorted Parameter Estimates

Like in previous analyses, missing the naval gun and having the Marte missile system equipped has the largest negative impact on performance. Additionally, the type of SFAC the OPVs are combating seems to have a larger impact since model performance seems to increase when OPVs are facing the slower type 1 SFAC. What seems to be more interesting is that the helicopter factor has been removed from model significance. This means that factors associated specifically to the OPV and the SFACs are what are most important for the MOP, and not the detection capability provided by the helicopter.

2. Aggressive SFACs vs. Baseline OPVs

If the SFAC avoidance behavior is reversed the SFACs become aggressive to the OPVs. The aggressive scenario tries to show OPV defensive performance in a hostile SFAC environment.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
OPV Gun Present[0]	-1.271576	0.017744	-71.66	<.0001*
OPV Missile Type[1]	-0.44646	0.017564	-25.42	<.0001*
Helo Present[0]	-0.240027	0.017509	-13.71	<.0001*
SFAC Type[1]*(OPVMaxSpeed-30.9714)	-0.020517	0.003373	-6.08	<.0001*
Helo Present[0]*SFAC Type[1]	-0.106842	0.017611	-6.07	<.0001*
SFAC Type[1]	-0.097253	0.017422	-5.58	<.0001*
OPV Gun Present[0]*OPV Missile Type[1]	-0.091033	0.017621	-5.17	<.0001*
Helo Present[0]*OPV Gun Present[0]	0.0834585	0.017467	4.78	<.0001*
OPV Radar Heights{13-22}*SFAC Type[1]	-0.084997	0.024461	-3.47	0.0006*
OPV Radar Heights{13-22}	-0.076548	0.024339	-3.15	0.0019*
OPVMaxSpeed	0.0098877	0.003348	2.95	0.0036*
OPV Radar Heights{16&19-13&22}	-0.018079	0.017929	-1.01	0.3146

Figure 44. Aggressive vs. Baseline Sorted Parameter Estimates

Figure 46 displays how the lack of a naval gun and use of the less capable missile system yields lower and lower measures of performance. Unlike in the Avoidance scenario however, the helicopter factor returns to be the third most significant factor followed by the interaction term of SFAC type and OPV maximum speed. The individual OPV maximum speed factor dropped significantly in its contribution to OPV performance. The reason behind this observation is that SFACs are now closing and engaging detected OPVs, which means OPVs are less likely to need to pursue their small boat targets.

3. Combination Avoidance & Aggressive SFACs vs. Baseline OPVs

The combination scenario introduces both the avoidance and aggressive SFAC agents to the simulation, and attempts to see how these varied behaviors impact OPV factor performance. This approach of a mixed SFAC threat has substantial credibility since strategies like these were employed by the Tamil Sea Tigers to break Sri Lankan naval blockades near the end of their civil war. Suicide attack craft would engage blockading forces in an attempt to get resupply ships through. Additionally, this may be a strategy employed by an asymmetric adversary to attack guarded, high value targets, such as naval aircraft carriers or oil platforms.

a. Avoidance SFAC Prosecution

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
OPV Missile Type[1]	-0.491378	0.016229	-30.28	<.0001*
OPV Gun Present[0]	-0.448231	0.01629	-27.52	<.0001*
OPV Radar Heights{22&19-16&13}	-0.195481	0.016256	-12.02	<.0001*
(OPV Radar Heights{22&19-16&13}+0.00503)*OPV Missile Type[1]	-0.191758	0.016478	-11.64	<.0001*
SFAC Type[1]	0.1880949	0.01627	11.56	<.0001*
OPV Missile Type[1]*SFAC Type[1]	0.1201119	0.016317	7.36	<.0001*
(OPV Radar Heights{22&19-16&13}+0.00503)*SFAC Type[1]	0.1112287	0.016335	6.81	<.0001*
(OPV Radar Heights{22-19}-0.01508)*OPV Missile Type[1]	-0.118707	0.023439	-5.06	<.0001*
OPV Radar Heights{22-19}	-0.118177	0.023467	-5.04	<.0001*
OPVMaxSpeed	0.0130586	0.003165	4.13	<.0001*
OPV Gun Present[0]*(OPVMaxSpeed-30.9714)	-0.012556	0.003147	-3.99	<.0001*
SFAC Type[1]*(OPVMaxSpeed-30.9714)	-0.012294	0.0032	-3.84	0.0002*
(OPV Radar Heights{22&19-16&13}+0.00503)*OPV Gun Present[0]	-0.039126	0.016382	-2.39	0.0179*
OPV Gun Present[0]*OPV Missile Type[1]	-0.012809	0.016289	-0.79	0.4327

Figure 45. Combination vs. Baseline: Avoidance SFAC Prosecution Sorted Parameter Estimates

In the combination scenario, factor importance takes a turn in significance from the naval gun to the equipped missile type when focusing on avoidance SFACs. Additionally, the OPV radar height, and its interaction with the missile type factor move up in importance for model performance. Reasons behind this change are due to the simulation environment, where OPVs initial engagement on avoidance SFACs is largely dependent on missile attacks and detection distance. As the simulation progresses, OPVs become hindered and overwhelmed by the attacking aggressive SFACs, and they no longer have the resources or ability to prosecute the avoiding SFACs to keep them from reaching the goal line.

b. Aggressive SFAC Prosecution

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
OPV Gun Present[0]	-0.510819	0.011059	-46.19	<.0001*
OPV Radar Heights{16&19&13-22}	-0.108935	0.01286	-8.47	<.0001*
(OPV Radar Heights{16&19&13-22}-0.48744)*OPV Missile Type[1]	-0.08246	0.012529	-6.58	<.0001*
SFAC Type[1]	-0.071093	0.01095	-6.49	<.0001*
OPV Missile Type[1]	-0.070638	0.01093	-6.46	<.0001*
Helo Present[0]	-0.055297	0.011061	-5.00	<.0001*
OPV Radar Heights{19-13}	0.0740784	0.01577	4.70	<.0001*
OPV Missile Type[1]*SFAC Type[1]	-0.042504	0.01105	-3.85	0.0002*
Helo Present[0]*SFAC Type[1]	-0.041385	0.011013	-3.76	0.0002*
(OPV Radar Heights{16&19&13-22}-0.48744)*OPV Gun Present[0]	-0.045356	0.012941	-3.50	0.0006*
(OPV Radar Heights{16-19&13}+0.25126)*OPV Gun Present[0]	-0.037262	0.013752	-2.71	0.0074*
(OPV Radar Heights{19-13}+0.01508)*Helo Present[0]	0.0337595	0.015565	2.17	0.0314*
OPV Radar Heights{16-19&13}	-0.024462	0.013775	-1.78	0.0774

Figure 46. Combination vs. Baseline: Aggressive SFAC Prosecution Sorted Parameter Estimates

In contrast to the factor importance shown in Figure 47, Figure 48 shows a return to the importance of the naval gun for the aggressive SFAC prosecution portion of the scenario. OPV radar height and its interaction with SSM type still play a large role in determining performance. As with the avoidance SFACs, the first engagement of the OPVs against the aggressive threat is via missile strikes, but as the problem progresses to a more close quarters fight, OPVs are forced to rely almost entirely upon their naval gun if equipped to fend off the suicide aggressive SFACs. If the gun is not equipped, OPVs are essentially defenseless once all missiles are expended, and are destroyed.

c. Avoidance & Aggressive SFAC Prosecution

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
OPV Gun Present[0]	-0.953348	0.015974	-59.68	<.0001*
OPV Missile Type[1]	-0.547443	0.015841	-34.56	<.0001*
SFAC Type[1]	0.1162076	0.01573	7.39	<.0001*
(OPV Radar Heights{19&16&22-13}-0.48744)*OPV Missile Type[1]	-0.108507	0.018897	-5.74	<.0001*
(OPV Radar Heights{19&16-22}-0.23116)*OPV Missile Type[1]	0.1029935	0.01945	5.30	<.0001*
OPV Missile Type[1]*SFAC Type[1]	0.0831372	0.015821	5.25	<.0001*
SFAC Type[1]*(OPVMaxSpeed-30.9714)	-0.016195	0.003135	-5.17	<.0001*
Helo Present[0]	-0.078944	0.015813	-4.99	<.0001*
OPV Gun Present[0]*(OPVMaxSpeed-30.9714)	-0.014152	0.003064	-4.62	<.0001*
OPV Radar Heights{19&16-22}	0.0874424	0.019373	4.51	<.0001*
(OPV Radar Heights{19&16&22-13}-0.48744)*SFAC Type[1]	0.081443	0.018477	4.41	<.0001*
OPV Radar Heights{19&16&22-13}	-0.080281	0.018328	-4.38	<.0001*
OPVMaxSpeed	0.0130101	0.003095	4.20	<.0001*
Helo Present[0]*SFAC Type[1]	-0.059155	0.015854	-3.73	0.0003*
(OPV Radar Heights{19-16}+0.00503)*SFAC Type[1]	0.0855746	0.023077	3.71	0.0003*
(OPV Radar Heights{19&16-22}-0.23116)*SFAC Type[1]	-0.072091	0.019454	-3.71	0.0003*
(OPV Radar Heights{19-16}+0.00503)*OPV Missile Type[1]	-0.080712	0.023138	-3.49	0.0006*
OPV Radar Heights{19-16}	-0.07792	0.023062	-3.38	0.0009*
OPV Gun Present[0]*SFAC Type[1]	-0.049668	0.016034	-3.10	0.0023*
(OPV Radar Heights{19-16}+0.00503)*Helo Present[0]	0.0655065	0.023158	2.83	0.0052*
(OPV Radar Heights{19&16-22}-0.23116)*Helo Present[0]	0.0510729	0.019161	2.67	0.0084*
OPV Gun Present[0]*OPV Missile Type[1]	-0.034508	0.01631	-2.12	0.0358*
Helo Present[0]*(OPVMaxSpeed-30.9714)	0.0003932	0.003086	0.13	0.8988

Figure 47. Combination vs. Baseline Sorted Parameter Estimates

When the previous two models resulting in Figure 47 and Figure 48 are combined, the subsequent factor significance is displayed in Figure 49. The naval gun still remains the most influential factor in determining OPV performance in the full combination scenario, but equipped SSM type is slightly more significant than in previous model scenarios, as in the specific avoidance or aggressive models. OPV radar height and interactions with missile type are very important in this environment since they largely dictate how the scenario proceeds at the beginning of a simulation run, which in turns helps to dictate how difficult the problem becomes for OPVs once SFACs begin to engage or avoid them. This particular scenario is somewhat more interesting than previous ones, because it begins to explore a more realistic threat in regards to the small boat swarm attack.

4. Avoidance SFACs vs. Enhanced OPVs

Given the challenging environment the baseline OPVs were placed in for the previous model scenarios, it is only fair to explore simulation outcomes with a more robust and capable OPV. These enhanced OPVs have several changes made to them to help them better combat the avoidance SFAC threat, which are detailed in Chapter III.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
SFAC Type[1]	0.7224214	0.029458	24.52	<.0001*
OPVMaxSpeed	0.1294463	0.005619	23.04	<.0001*
Helo Present[0]	0.2939655	0.029363	10.01	<.0001*
SFAC Type[1]*(OPVMaxSpeed-30.9714)	0.0466665	0.005688	8.20	<.0001*
OPV Missile Type[1]	-0.192788	0.029732	-6.48	<.0001*
Helo Present[0]*SFAC Type[1]	-0.190675	0.029438	-6.48	<.0001*
(OPV Radar Heights{19&13-22}-0.24121)*SFAC Type[1]	-0.164899	0.035272	-4.68	<.0001*
(OPVMaxSpeed-30.9714)*(OPVMaxSpeed-30.9714)	-0.004724	0.00121	-3.90	0.0001*
OPV Gun Present[0]	-0.113292	0.029568	-3.83	0.0002*
(OPV Radar Heights{19-13}+0.01508)*SFAC Type[1]	0.1512115	0.042536	3.55	0.0005*
Helo Present[0]*(OPVMaxSpeed-30.9714)	-0.018707	0.005642	-3.32	0.0011*
(OPV Radar Heights{19&13&22-16}-0.50754)*(OPVMaxSpeed-30.9714)	0.0206967	0.006861	3.02	0.0029*
(OPV Radar Heights{19-13}+0.01508)*(OPVMaxSpeed-30.9714)	0.0234651	0.00786	2.99	0.0032*
OPV Radar Heights{19&13-22}	-0.032904	0.0355	-0.93	0.3552
OPV Radar Heights{19&13&22-16}	-0.015526	0.03509	-0.44	0.6587
Helo Present[0]*OPV Missile Type[1]	-0.011524	0.029456	-0.39	0.6961
OPV Radar Heights{19-13}	-0.015798	0.041526	-0.38	0.7041

Figure 48. Avoidance vs. Enhanced Sorted Parameter Estimates

With the modifications to the naval gun being in effect, its significance drops sharply for OPV performance, and now the problem is more reliant upon the SFAC type and OPV maximum speed. This result has more credibility when referencing documents concerning the Sri Lankan Civil War and the Iranian Naval Warfare Doctrine (Haghshenass, 2006). The helicopter factor also plays a large role in OPV performance, because tactical data being fed to the OPVs helps to dictate their motion given the need to pursue the avoiding SFAC threat. This result diverges from the previous avoidance scenario which excluded the helicopter factor.

5. Aggressive SFACs vs. Enhanced OPVs

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
OPV Radar Heights{13-16&19&22}	-0.004117	0.000562	-7.32	<.0001*
(OPV Radar Heights{13-16&19&22}+0.48744)*SFAC Type[1]	-0.003752	0.00056	-6.70	<.0001*
SFAC Type[1]	-0.002777	0.000487	-5.70	<.0001*
(OPV Radar Heights{13-16&19&22}+0.48744)*Helo Present[0]	-0.002787	0.000562	-4.96	<.0001*
Helo Present[0]	-0.002075	0.000489	-4.25	<.0001*
Helo Present[0]*SFAC Type[1]	-0.002019	0.000489	-4.13	<.0001*

Figure 49. Aggressive vs. Enhanced Sorted Parameter Estimates

Quite possibly the most surprising outcome of the enhanced OPV scenarios is the aggressive SFAC threat. As seen in Figure 51, the only contributing factor specific to the OPV is its detection capability, represented by the radar height and helicopter factor. The helicopter is less important that the OPV radar height. This result is similar to the previous aggressive SFAC scenario, because OPVs are not required to pursue SFAC threats as much as in the avoidance scenarios, since SFACs detect and attempt to collide with OPVs. Also, since the Griffin missile system is included on all OPVs its effectiveness is driving down the significance of the surface to surface missile capability and the naval gun. While the assumptions made about the effectiveness of the Griffin missile system are still under evaluation, a comparable weapon system proposed in Cobian (2002), may have a similar impact on OPV performance.

6. Combination Avoidance & Aggressive SFACs vs. Enhanced OPVs

a. Avoidance SFAC Prosecution (Enhanced OPVs)

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
SFAC Type[1]	0.7723136	0.019143	40.34	<.0001*
OPV Missile Type[1]	-0.440996	0.01926	-22.90	<.0001*
OPVMaxSpeed	0.0763678	0.003754	20.34	<.0001*
OPV Missile Type[1]*SFAC Type[1]	0.2378455	0.019673	12.09	<.0001*
(OPV Radar Heights{22-13&19&16}+0.48744)*OPV Missile Type[1]	-0.257776	0.022749	-11.33	<.0001*
(OPV Radar Heights{19-16}+0.00503)*SFAC Type[1]	0.2185977	0.028427	7.69	<.0001*
SFAC Type[1]*(OPVMaxSpeed-30.9714)	-0.028068	0.003805	-7.38	<.0001*
OPV Radar Heights{22-13&19&16}	-0.156836	0.022052	-7.11	<.0001*
OPV Gun Present[0]	-0.130516	0.019467	-6.70	<.0001*
(OPV Radar Heights{19-16}+0.00503)*OPV Missile Type[1]	-0.143313	0.028478	-5.03	<.0001*
(OPV Radar Heights{13-19&16}+0.23116)*OPV Missile Type[1]	0.1190595	0.024034	4.95	<.0001*
(OPV Radar Heights{13-19&16}+0.23116)*SFAC Type[1]	-0.108155	0.023542	-4.59	<.0001*
(OPV Radar Heights{13-19&16}+0.23116)*(OPVMaxSpeed-30.9714)	-0.018208	0.004507	-4.04	<.0001*
(OPV Radar Heights{22-13&19&16}+0.48744)*(OPVMaxSpeed-30.9714)	0.0175123	0.004369	4.01	<.0001*
(OPVMaxSpeed-30.9714)*(OPVMaxSpeed-30.9714)	-0.003213	0.000805	-3.99	<.0001*
OPV Radar Heights{19-16}	-0.097176	0.028021	-3.47	0.0007*
(OPV Radar Heights{22-13&19&16}+0.48744)*SFAC Type[1]	0.0760141	0.022321	3.41	0.0008*
Helo Present[0]	-0.060362	0.019353	-3.12	0.0021*
OPV Radar Heights{13-19&16}	-0.047509	0.023605	-2.01	0.0457*
Helo Present[0]*OPV Gun Present[0]	0.015705	0.019765	0.79	0.4279

Figure 50. Combination vs. Enhance: Avoidance SFAC Prosecution Sorted Parameter Estimates

For the first portion of the combination vs. enhanced OPV scenario, avoidance SFAC prosecution relies more on the type of SFACs being engaged, and the missile system equipped on the OPVs. As in the previous combination scenario, the majority of avoidance SFACs are prosecuted by the longer range missile systems rather than the naval gun or griffin missile system. The reason behind this is, again, that aggressive SFACs engage the OPVs. Their influence in the simulation environment serves as both a distraction and a potential threat that must be dealt with prior to OPVs continued engagement of avoiding SFACs. Other important factors to note are OPV max speed and radar height interactions with missile and SFAC type. These three factors help to position OPVs where they can best prosecute the SFAC threat, both the attacking and evading small boats.

b. Aggressive SFAC Prosecution (Enhanced OPVs)

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
OPV Radar Heights{13-16&19&22}	-0.003901	0.000696	-5.61	<.0001*
(OPV Radar Heights{13-16&19&22}+0.48744)*SFAC Type[1]	-0.003636	0.000696	-5.23	<.0001*
SFAC Type[1]	-0.002269	0.000607	-3.74	0.0002*

Figure 51. Combination vs. Enhanced: Aggressive SFAC Prosecution Sorted Parameter Estimates

Mirroring the first portion of the results shown in Figure 51, the parameter estimates displayed in Figure 53 indicate that the most important and only significant factor in determining OPV performance for aggressive SFAC prosecution in the combined scenario is OPV radar height. The type of SFAC engaged is also significant, but as far as controllable factors for the OPV, the detection capability of the OPV, influenced by its radar height, is the key factor to consider. This result reflects many of the same conditions seen in the Aggressive SFAC vs. Enhanced OPV scenario because OPV max speed, SSM equipped, and naval gun are eclipsed by the behavior of attacking SFACs and the Griffin missile system. The helicopter factor is negligible as well since all engagements with aggressive SFACs take place within OPV radar detection ranges, so it is unnecessary for this scenario.

c. Avoidance and Aggressive SFAC Prosecution (Enhanced OPVs)

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
SFAC Type[1]	0.7702053	0.019111	40.30	<.0001*
OPV Missile Type[1]	-0.440329	0.019228	-22.90	<.0001*
OPVMaxSpeed	0.0763699	0.003748	20.38	<.0001*
OPV Missile Type[1]*SFAC Type[1]	0.2385031	0.019641	12.14	<.0001*
(OPV Radar Heights{22-13&19&16}+0.48744)*OPV Missile Type[1]	-0.258481	0.022711	-11.38	<.0001*
(OPV Radar Heights{19-16}+0.00503)*SFAC Type[1]	0.2192686	0.02838	7.73	<.0001*
SFAC Type[1]*(OPVMaxSpeed-30.9714)	-0.027965	0.003799	-7.36	<.0001*
OPV Radar Heights{22-13&19&16}	-0.154772	0.022015	-7.03	<.0001*
OPV Gun Present[0]	-0.131564	0.019435	-6.77	<.0001*
(OPV Radar Heights{19-16}+0.00503)*OPV Missile Type[1]	-0.144166	0.028431	-5.07	<.0001*
(OPV Radar Heights{13-19&16}+0.23116)*OPV Missile Type[1]	0.1201348	0.023995	5.01	<.0001*
(OPV Radar Heights{13-19&16}+0.23116)*SFAC Type[1]	-0.111738	0.023503	-4.75	<.0001*
(OPV Radar Heights{13-19&16}+0.23116)*(OPVMaxSpeed-30.9714)	-0.018129	0.0045	-4.03	<.0001*
(OPVMaxSpeed-30.9714)*(OPVMaxSpeed-30.9714)	-0.003239	0.000804	-4.03	<.0001*
(OPV Radar Heights{22-13&19&16}+0.48744)*(OPVMaxSpeed-30.9714)	0.0175104	0.004362	4.01	<.0001*
(OPV Radar Heights{22-13&19&16}+0.48744)*SFAC Type[1]	0.0776727	0.022284	3.49	0.0006*
OPV Radar Heights{19-16}	-0.096654	0.027975	-3.46	0.0007*
Helo Present[0]	-0.060073	0.019321	-3.11	0.0022*
OPV Radar Heights{13-19&16}	-0.051472	0.023566	-2.18	0.0303*
Helo Present[0]*OPV Gun Present[0]	0.0160047	0.019733	0.81	0.4184

Figure 52. Combination vs. Enhanced Sorted Parameter Estimates

The final analysis concerning enhanced OPV factor importance is displayed in Figure 54, and it is almost an exact replica of Figure 52. What this implies is that the avoidance portion of the combination scenario drives the factor importance for the OPVs. This result makes sense given the weak factor significance shown in Figure 53. SFACs employing the avoidance behavior present the largest challenge for OPVs in this scenario, so it is the factors inherent to that portion of the simulation that drive the results. SFACs employing the aggressive behavior charge the OPVs to their own demise, unable to impact OPV behavior for long due to the effectiveness of the ROC behavior provided to OPVs and the effectiveness of the Griffin missile system.

E. FACTOR DIFFERENCES

1. Naval Gun

In contrast to the baseline results, and many of the advanced scenario results utilizing the baseline OPV parameters, the naval gun loses its significance in the enhanced OPV models. This is due to both the inclusion of weapons, such as the Griffin missile which is specifically designed to eliminate the SFAC threat, and the modeling of the naval gun to more accurately reflect the effectiveness of naval gunfire at sea. During the Second World War, naval gunfire was being eclipsed by other modes of combat at sea. Then it was the carrier borne attack fighter, capable of guiding munitions and torpedoes at far greater ranges than those capable by guns of the time. Today they are further diminished in their use by radar and sensor guided munitions which can have ranges an order of magnitude higher than naval gunfire, and are far more accurate. Naval gunfire is much more limited than missile capabilities, and while its relevance on ships today is still debated, for these simulations the naval gun takes second seat to missile systems such as the Anti-Ship Cruise Missile (ASCM) or self-defense guided missile like the Griffin.

2. Surface to Surface Missile

Unlike the decline in importance shown by the naval gun, equipped missile type continues to play a big role in determining OPV measures of performance. The long range and high probability of kill outlined in the provided scenario briefings by the OSN staff establish a weapon system very capable of combating a small boat threat. Its only drawback is the availability of ammunition on the OPVs. Missiles like the Exocet are very large, expensive, and their employment at sea takes up significant deck space on current naval warships. Since these models did not address the ship synthesis problem inherent with fielding ASCMs, their use is somewhat questionable. However, their effectiveness in model performance is not, and the SSM factor remains a key operational design parameter for ship measures of performance.

3. OPV Radar Height

Unlike in the baseline scenarios, the OPV radar height factor becomes very significant in combating the avoidance and aggressive SFAC threat. OPVs facing the swarm attack of suicide SFACs must rely on organic capabilities to defend themselves at times, and the further that they can detect this threat the greater their survivability. This importance is not seen so much in the individual radar height factor, but in the interactions between OPV missile type, SFAC type, and OPV speed. These interactions help to paint a picture that the OPV radar height is a system that would integrate with many different facets of shipboard operations to create an effective fighting vessel.

4. OPV Max Speed

The OPV maximum speed factor largely remained a modest contributor to OPV measures of performance. Only in the Avoidance SFAC vs. Enhanced OPV and Combination scenarios did OPV maximum speed become a much more significant factor. The reason behind this was due to the effectiveness of ROC behavior by the OPVs, and the Griffin missile system. OPVs could easily avoid attacking SFACs in the combination scenario and subsequently continue to pursue evading SFACs to increase their measure of performance. While a large repertoire of weapon systems may negate the need of a quick and agile ship, the costs associated with such an increase may be prohibitive. Abel’s thesis concerning frigate survivability illustrated that if ships were quick enough, they could evade attacking swarms of small boats (Abel, 2009), thus showing how important speed can be to ship survival in an ASUW environment.

5. Helicopter Presence

Much like in the OPV radar height factor, the presence of a helicopter played a moderate role in the OPV measure of performance of SFAC kills, but steadily grew in significance for the enhanced model runs. The reason behind this increase in effectiveness was the allowance of long range engagements by OPVs at the onset of a simulation run. With this increase in detection capability, OPVs could quickly eliminate a large number of the SFAC threat prior to engaging with the naval gun or Griffin missile system. As with the radar height factor, interaction terms with helicopter presence such as SFAC type and SSM type became prevalent with OPV performance since OPVs could maneuver quickly to engage the SFAC threat early in the simulation.

6. SFAC Type

The type of threat that OPVs were facing has always been a significant contributor to the OPV MOE and MOP. In both the baseline and advanced model simulations, the parameters changed with the shifting of SFAC type from one to the next always had a strong influence. Since these parameters impacted detection range and speed at which SFACs traveled, they had conflicting effects at times. In the aggressive scenarios, the larger SFAC would be detected at longer ranges, thus allowing OPVs to engage them earlier. However, their increased speed had a counter effect on OPV performance because these same SFACs would close the distance quicker on OPVs and possibly eliminate them from the simulation. For the avoidance scenarios, smaller SFACs may be harder to detect than the larger variants, but their reduced speed made it difficult for them to avoid pursuing OPVs. This trade-off between detection range and speed seemed to lean toward SFAC speed being the more significant detractor from OPV performance, and this is shown in various interaction terms as well as the leverage plots in the baseline analysis.

V. CONCLUSION

A. SUMMARY

This research study explored the simulation modeling effort behind operational effectiveness models which provide information to decision makers about naval ship design. Focused on the Anti-Surface Warfare scenario, the models generated during the course of this thesis were intended to determine key performance factors of hypothetical Offshore Patrol Vessels in their defense against the small boat swarm attack. The simulation platform used to explore this work was MANA, which utilizes an influence system to alter agent behaviors in the model. These behaviors and established parameters were varied and adjusted to help create an understanding of which design factors are of key importance to the ever evolving and changing problem of the small boat attack.

B. RESEARCH QUESTIONS

The following research questions were presented in the first chapter of this thesis:

1. Based on the limited number of design parameters of the OPV in the OSN model, can a model be produced in the MANA environment to replicate similar results?

2. Given the creation of this initial MANA model of the OPV's ASUW scenario, can additional variables be introduced to determine a better Operational Evaluation Model for OPV performance and subsequent input into the Ship Synthesis Model and cost models?

With the analysis conducted in Chapter IV, it was shown that it was indeed possible to replicate a model in MANA which behaved very similarly to the OSN agent based model. While slight differences were present, over 98% of all variation between the two models was accounted for, and all interactions terms with the Indicator[Italian] variable were deemed insignificant, and therefore removed.

The results generated by having an interchangeable MANA baseline model helped to create a basis for comparison between baseline factor significance to later determine advanced model results.

Addressing the second question, it was shown through a series of model improvements that key determinants of model performance did change, and that the resulting insights created a more realistic set of factors for decision makers to focus on in ship development. These factors agree with findings from historical records concerning the small boat swarm threat, and support current published naval doctrine by nations in highly tense regions of the world.

C. RECOMMENDATIONS & FUTURE WORK

Given the constrained modeling parameters provided by the OSN ASUW scenario, exploration of a larger set of decision factors that influence measures of effectiveness and measures of performance may be of significant worth. This study was part of an effort by students and faculty at NPS to support and verify practices undertaken by OSN, as directed by ONR. Expanding upon the design space of the models created in this thesis may help to gather better insight on key performance factors which can then in turn be placed into decision tools to aid in ship design. Additionally, incorporating more real world systems and characteristics of modern naval warships may also be of use. To further the realism of the scenarios presented, the inclusion of noise factors, such as sea-state, weather, and obstacles, may also improve understanding of this complex problem.

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